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Journal
Journal of experimental psychology. General, 149(8)

ISSN
0096-3445

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Publication Date
2020-08-01

DOI
10.1037/xge0000719

Peer reviewed

Is Social Decision Making for Close Others Consistent Across Domains and Within Individuals?

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Abstract

Humans make decisions across a variety of social contexts. Though social decision making research has blossomed in recent decades, surprisingly little is known about whether social decision making preferences are consistent across different domains. We conducted an exploratory study in which participants made choices about two types of close others, parents and friends. To elicit decision making preferences, we pit the interests in parents and friends against one another. To assess the consistency of preferences for close others, decision making was assessed in three domains—risk taking, probabilistic learning, and self-other similarity judgments. We reasoned that if social decision making preferences are consistent across domains, participants ought to exhibit the same preference in all three domains (i.e., a parent preference, based on prior work), and individual differences in preference magnitude ought to be conserved across domains within individuals. A combination of computational modeling, random coefficient regression, and traditional statistical tests revealed a robust parent-over-friend preference in the risk taking and probabilistic learning domains—but not the self-other similarity domain. Preferences for parent-over-friend in the risk taking domain were strongly associated with similar preferences in the probabilistic learning domain, but not the self-other similarity domain. These results suggest that distinct and dissociable value-based and social cognitive computations underlie social decision making.

Keywords: Social Decision Making; Risk taking; Probabilistic Learning; Self-Other Similarity

Is Social Decision Making for Close Others Consistent Across Domains and Within Individuals?

Human beings embed themselves in rich social environments (Hill & Dunbar, 2003; Rand, Arbesman, & Christakis, 2011). One implication of our social complexity is that the decisions we make often have consequences for those closest to us. Knowing how individuals make decisions when multiple close others are affected is useful because it can reveal how close relationships are prioritized with respect to one another (Knoll, Magis-Weinberg, Speekenbrink, & Blakemore, 2015; Welborn et al., 2015). Yet, most social decision making studies have historically focused on decisions affecting a socially distant confederate, constraining the ecological validity of their findings. Moreover, it is unknown whether preferences between close others are preserved across different domains—for example, those marked by probabilistic demands and changing contingencies versus how similarly we judge others to be to ourselves. Together, these gaps undermine our ability to craft a unifying theory about both social preferences and social decision making. The current work addresses this issue by testing whether other-oriented social decision making preferences are systematically preserved across multiple domains. In a pair of exploratory and confirmatory studies, we attempt to (i) replicate prior work showing that young adults favor a parent over a friend when making other-oriented social decisions in the risk taking domain (Guassi Moreira, Tashjian, Galván, & Silvers, 2018), (ii) determine whether this preference generalizes to another decision making domain—one involving probabilistic learning demands—(iii) test if said preferences persist in a domain abstracted away from concrete decision making behavior (e.g., when defining representations of self and others), and (iv) determine whether individual differences in preference magnitude are consistent across these three domains.

Understudied Facets of Social Decision Making. Psychological science and related fields have long been interested in characterizing the motivational underpinnings of goal-directed behavior (e.g., Atkinson, 1957; Hull, 1931; Rotter, 1960). More recently, efforts have been made to examine goal-directed decision making in social contexts (Crockett, Kurth-Nelson, Siegel, Dayan, & Dolan, 2014; Feldmanhall & Chang, 2018; Wills, Hackel, & Van Bavel, 2018). Despite the substantial progress made in understanding social decision making, there remain a number of open questions. First, much of the extant social decision making research has examined how people make decisions that directly impact themselves and unfamiliar, distant others such as a confederate (Lockwood et al., 2017; Volz, Welborn, Gobel, Gazzaniga, & Grafton, 2017). Although a few notable studies have been recently published investigating topics such as making decisions on the behalf of one’s in-group (Edelson, Polania, Ruff, Fehr, & Hare, 2018), or processing rewards for others (Braams & Crone, 2016), or using information about perceived preferences of others for decision making (Harris, Clithero, & Hutcherson, 2018), comparatively less work overall has been devoted to understanding how individuals make decisions that have consequences for close others. Second, studies rarely examine how individuals make decisions that stand to impact multiple individuals in competing ways (i.e., benefit one close other and hurt another). Last, little research has worked to establish whether social decision making tendencies are consistent across domains (de Oliveira, Eckel, & Croson, 2012), in part because so much contemporary research in this area has leaned heavily on the same well-vetted models of risky decision making (e.g., Prospect Theory; Tversky & Kahneman, 1992). This final topic is perhaps the most understudied of the three. While it is well established that decision making often differs dramatically across different domains, little to no work has examined whether decision making in one social context transfers to another. Examining how preferences persist or differ across contexts stands to inform our understanding of how stable individual differences in decision making are as well as providing broad information about how individuals value and prioritize different social relationships.

Recent research suggests that people adapt their decision making behavior when close others stand to gain or lose. For example, adolescents—who are particularly sensitive to social feedback relative to children and adults (Blakemore & Mills, 2014)—appear to adjust decision making behaviors when close others such as friends and parents are affected by their actions (Guassi Moreira & Telzer, 2018; Powers et al., 2018). Other work has indicated that individuals prioritize multiple close others differently, as evidenced by another recent study that showed young adults favor parents over friends when making decisions that benefit one close other at the expense of the other (Guassi Moreira et al., 2018). However, it remains unknown whether social decision making preferences are consistent across domains, and whether individuals consistently endorse preferences across domains. We sought to address these questions in the current study by examining whether other-oriented preferences in social decision making generalize to probabilistic learning and self-other similarity judgments. We further examine how within-subject behavior in one domain tracks with behavior in another.

Examining Other-Oriented Social Decision Making Preferences in the Probabilistic Learning Domain. Individuals are commonly required to make sense of probabilistic and changing contingencies (Behrens, Woolrich, Walton, & Rushworth, 2007; Navarro, Tran, & Baz, 2018; White & Monosov, 2016). Many social behaviors are dynamic and more often than not, are characterized by ambiguity and uncertainty (Kohls et al., 2013; Rilling & Sanfey, 2011; Sanfey, 2007). As such, probabilistic learning models may be one of the most effective ways to understand how humans navigate their complex and changing social ecologies. A reinforcement learning framework may be particularly useful in describing social decision making preferences given their broad success in explaining other learning (Rescorla & Wagner, 1972) and psychological phenomena (Jara-Ettinger, 2019; Pynadath, Rosenbloom, & Marsella, 2014).

To date, however, relatively little is known about social decision making in the probabilistic learning domain. Existing research shows that individuals readily learn about probabilistic, changing reward contingencies for themselves and non-familiar others (e.g., a charity), display marked individual differences in how they prioritize others compared to themselves (i.e., differential motivations for self versus other reward), and these tendencies reliably track with self-reports of real-world social decision making (Kappes et al., 2018; Kwak & Huettel, 2016; Kwak, Pearson, & Huettel, 2014). Despite the advances of this foundational work, it is still unknown whether differences in social decision making preferences exist when close, rather than distant, others are affected and, more importantly, if preferences from other domains (e.g., such as risk taking) reliably manifest themselves in the probabilistic learning domain. This gap is important to address for a number of reasons. First, if preferences generalize between domains, it would suggest that fundamental social cognitive and affective processes support social decision making behavior across multiple contexts in service of social preferences. Second, learning from past rewards is an implicit process which is meaningfully different from other, more explicit models of social decision making (Kwak & Huettel, 2016). If individuals hold the same preferences (e.g., parent over friend) in a domain that requires implicit processes (e.g., probabilistic learning) compared to explicit processes (e.g., see prior work in the risk taking domain: Guassi Moreira et al., 2018), this would provide further evidence that social preferences support intuitive, in addition to effortful, psychological processes (e.g., Carlson, Aknin, & Liotti, 2016; Wills et al., 2018). This would speak to the importance of certain close relationships, that said relationships influence spontaneous and implicit processes to drive goal pursuit in their favor. Last, probabilistic learning most closely simulates the psychological ecology that individuals navigate in their everyday lives. Though undoubtedly useful, relying exclusively on highly controlled, but inherently static, experimental social decision making paradigms may hamper generalizability and construct validity. For these reasons, we viewed probabilistic learning as an important domain with which to conduct a cross-domain examination.

Examining Other-Oriented Social Decision Making Preferences in the Self-Other Similarity Judgments Domain. Humans possess a remarkable capacity to construct richly detailed representations of social agents (Amodio, 2019; Chavez, Heatherton, & Wagner, 2017; Hassabis et al., 2014; Wang et al., 2017). Social cognitive processes that spur social behavior rely heavily on these representations, and particularly how much overlap exists between one's self-representation and one's representation of another individual (Amodio, 2019; Tajfel & Turner, 1979). In turn, correspondence between one's self-representation and their representations of others tends to be highly consequential for behavior (e.g., Tajfel & Turner, 1979). For instance, individuals frequently favor those who they deem more similar to themselves, behaving in accordance to evolutionary and developmentally conserved drives to reward, and affiliate with, similar others (Hamlin, Mahajan, Liberman, & Wynn, 2013; Pun, Ferera, Diesendruck, Hamlin, & Baron, 2018; Van Bavel, Packer, & Cunningham, 2008).

How similarly one judges another person to be to oneself can significantly impact social perception, intergroup dynamics and moral judgments (Hackel, Zaki, & Van Bavel, 2017; Tajfel & Turner, 1979; Van Bavel et al., 2008; Yoder & Decety, 2018). However, less is known about how judgments of self-other similarity affect social decision making. This knowledge gap precludes a deeper understanding of how representations inform social judgments and affect preferences. Understanding how self-other judgment similarity relates to social decision making may help determine whether social decision making preferences are largely affiliative—that is, behavior is driven by motivations stemming from the relationship itself— or instrumental—the relationship is an instrument used to achieve a different goal—in nature. If judging an individual to be similar to oneself predicts social preferences for that individual, that would suggest that individuals make social decisions due to affiliative motives. On the other hand, if no relationship is observed between self-other judgment similarity and social preferences, that suggests that a different mechanism may be driving social decision making. These notions underscore the benefit of studying self-other similarity judgments for social decision making research.

Examining Whether Other-Oriented Social Decision Making Preferences Remain Consistent within Individuals. Another poorly understood feature of social decision making is whether preferences are conserved *within* participants. Though apparently subtle, this distinction is crucial: A group level preference may consistently emerge across domains, but it is not guaranteed that individuals who show a particular preference in one domain show that same preference in another domain (e.g., Seaman et al., 2018). This work is necessary in order to parse domain-specific and domain-general contributions to other-oriented social decision making behavior, and to examine how preferences track across domains. As illustrated above, very little work has directly compared social decision making preferences across multiple domains, and even less work has done so within the same research participants. We sought to address this open issue in the present study, in part because doing so may reveal latent psychological substrates and help eventually generate a unified model of decision making.

Understanding links between different domains may prove to be especially useful for improving the ecological validity of social decision making research. This is in part because real life decision making – for example, deciding whether to spend one's weekend with family versus friends – are often colored with computations of risk, learning, and self-other judgments that do not neatly compartmentalize into the categories used by scientists. Studying these three domains in tandem is apt given that many everyday decisions have elements of risk and uncertainty (White & Monosov, 2016), while similarity judgments may bias the extent to which individuals are motivated to consider reward contingencies and potential risks when making decisions with implications for closer others (Dunham, 2018).

Overview of Current Studies. Study 1 was an exploratory endeavor intended to lay a foundation for later confirmatory studies addressing the issues above. We set out to accomplish four research aims in Study 1. First, we aimed to directly replicate our prior findings showing that young adults prioritize parents over friends in a risky decision making context (Guassi Moreira et al., 2018). Second, we sought to explore whether parent-over-friend preferences would also emerge in the probabilistic learning domain. Third, we tested whether parent-over-friend preferences were also present in a more abstract decision making domain, self-other similarity judgments (see Figure 1, rows A and B, for a conceptual overview of the study's premise). Though we expected to see a parent-over-friend preference across all three domains, we did not pre-register hypotheses associated with these second and third aims because they are exploratory. Last, we tested to see whether individual differences in parent versus friend preferences were consistently present across all three domains (risky decision making, probabilistic learning, and self-other similarity judgments). An ancillary aim to the study was examining the impact that subjective relationship quality had in shaping decision making preferences. Although this was a lesser aim, we report results with relationship quality throughout for the purposes of replicating prior work (Guassi Moreira et al., 2018) and to address a potential mechanism underlying our findings. With exploratory results in hand, Study 2 was then conducted to confirm the results of Study 1 in a larger, independent sample.

Study 1.

Methods

Participants. Participants in the current study were comprised of late adolescents and young adults recruited from the metropolitan West Los Angeles area using the University of California, Los Angeles' (UCLA) undergraduate psychology subject pool. Our focus on this age group is motivated by heighted needs for social affiliation and fluid social milieus occurring during this developmental stage (Arnett, 2014), making this an ideal population to study other-oriented social decision making behavior. Given that this study was exploratory in nature, we arbitrarily set our sample size at approximately fifty participants before the end of the 2018 Spring Quarter. Forty-nine participants were run through our protocol during May and June of 2018. Three participants were excluded from the reported analyses—one had difficulty following instructions (especially when nominating a parent and friend), and two were experiencing physical illness to an extent that adversely impacted their ability to concentrate on research activities. Our final sample included 46 participants (31 female, Mean age = 20.17 years, SD = 1.34, range = 18-23). Ethnically, 27% of participants identified as Hispanic/Latinx. Racially, 39% of participants identified as Asian, 27% percent of participants identified as White, 4% of participants identified as being mixed race, 2% identified as African American, 0% identified as Native Hawaiian/Pacific Islander, 0% identified as American Indian/Alaska Native, 12% identified as 'Other', and 16% declined to respond. All participants were compensated with course credit and provided written consent in accordance with the policies of the UCLA Institutional Review

Board. All data and materials are publicly available on the Open Science Framework (OSF; osf.io/534mz).

Procedure

Participants used UCLA's subject pool website to enroll in the present study, which was branded as a social decision making study. Upon arriving at the lab, participants were greeted by an experimenter, provided the informed consent needed to participate, nominated a parent and close friend, completed self-report instruments, and finally completed a series of computer tasks. Key measures of interest are detailed below; additional measures and their accompanying analyses are described in the Supplement. Participants were trained extensively by an experimenter on how to complete each task immediately before completing it; the experimenter did not begin a task until the participant demonstrated a proper understanding of the present task. The experimenter unobtrusively monitored the participant during the session to ensure compliance and answer questions as necessary.

Measures

Parent—Friend Nomination and Salience Procedure. Prior to completing any research activities, participants were asked to nominate any one parent and one close friend of their choice. To heighten the salience of completing several other-oriented decision-making tasks for close others that were not actually present, we instructed participants to fill out a form requiring them to write down a memory they had with—and a handful of words and phrases describing—their nominated parent and friend.

Parent and Friend Relationship Quality. Following the nomination, participants completed a slightly modified version of the Inventory of Parent and Peer Attachment (IPPA; Armsden &

Greenberg, 1987). We collected this measure chiefly for (i) the purposes of replicating our prior findings and (ii) because, as we mention above, it may be one way to account for individual differences in social decision making preferences observed in similar studies (Bouwmeester et al., 2017; Kwak et al., 2014). The measure is frequently used to assess subjective relationship quality in adolescent and young adult populations (e.g., Noftle & Shaver, 2006). The measure was amended to ask about the particular parent and friend nominated by the participant rather than parents and friends in general. A five-point Likert scale was used to answer 28 questions related to parent relationship quality (e.g., "My parent accepts me as I am") and 25 questions related to friend relationship quality (e.g., "My friend senses when I'm upset about something"). The measure in our sample displayed excellent reliability (α-Parent: 0.94; α-Friend: .92).

Columbia Card Task. Consistent with our prior work, we used a modified version of the 'hot' Columbia Card Task (CCT) to assess other-oriented decision making preferences under conditions of risk (Figure 1, row C, first schematic). During each round of the CCT, a set of overturned cards are displayed and participants were told that each card is either associated with a gain ('gain cards') or loss ('loss cards') of points. Participants were notified the purpose of the task is to win points by iteratively turning over cards. During each round, participants had the choice to turn over a card or to pass. If a gain card is turned over, participants had the opportunity to turn over another card or to pass; if a loss card is flipped, the round is over. One can pass at any point, which also ends the round and prohibits them from turning over additional cards in that set. Above the set of cards was a header that listed information about the current set of cards (e.g., number of loss cards, value of gain cards, etc.). Notably, because information about each deck is provided to participants and there is clearly a risky (flipping over a card, associated with variability in outcome) and non-risky (passing, associated with no variability in outcome) choice, this task was ideal for testing social decision making preferences in the risk taking domain. Participants completed two runs (each consisting of 24 rounds). On one run, participants were told to play as if all the rewards from gain cards benefitted their parent, while all the losses were incurred by their friend. On another round, participants were told to play as if the opposite were true (friend gain, parent loss). This manipulation ensures there was always a trade-off in prioritizing one close other at the expense of the second close other. Run order was counterbalanced across participants. Though participants were playing for hypothetical rewards (i.e., points), they were explicitly asked to make decisions as if the points could be redeemed for material goods or services (e.g., money, concert tickets, groceries, etc.). Thus, participants were instructed to play as if their decisions had tangible real-world outcomes. For further details, see Guassi Moreira et al. (2018). Due to technical difficulties, CCT data were unable to be recorded for one female participant, meaning that any results using this task reflect N = 45.

Social Gambling Task. In order to assess other-oriented preferences in probabilistic learning, we employed the Social Gambling Task (SGT; Figure 1, row C, second schematic) (Kwak et al., 2014). During each trial, participants were prompted to draw from one of four colored decks in order to earn a reward (e.g., points) for their parent and friend. Each deck was associated with a unique reward contingency, compromising a 2x2 fully orthogonal design (P+/F+, P+/F-, P-/F+, P-/F-; P = Parent, F = Friend, + = positive expected value, - = negative expected value). Positive expected values were associated with a 70% chance of winning points and a 30% chance of losing points whereas negative expected values were associated with the opposite (70% loss, 30% win). Losses were always set to the value of -1 points; parent and friend wins were set to +1 points in the P+/F+ deck; parent wins were set to +2 points and friend wins were set to +1 point in the P+/F- deck; friend wins were set to +2 and wins for parents were set to +1 point in the P-

/F+ deck. The expected values of each deck were therefore 0.4 points for parents and friend in the P+/F+ deck, -0.4 points for parents and friends in the P-/F- deck, and 1.1 points for parents/friends in the respective P+/F- / P-F/+ decks and -0.4 points for friends/parents in the respective P+/F- / P-F/+ decks. This design choice ensured the task would be incentive compatible. That is, because there was an opportunity cost for choosing the P+/F+ deck over either of the P+/F- or P-/F+ alternatives, participants with strong parent or friend preferences were incentivized to reveal said preferences. Because the SGT's decks each had a reward contingency that required feedback and experience to understand, and all decks had comparable levels of risk involved, this task was best suited to tap probabilistic learning in the context of social decision making. Just like with the CCT, participants were asked to treat these decisions as if they were consequential and not hypothetical (e.g., play as if points could be redeemed for material goods/services). Cumulative point totals for parents and friends were displayed at the top of the computer screen. Participants completed 150 trials, and the identities of each deck switched every 50 trials in order to ensure active learning was being measured during the majority of the task. Based on their response data, three participants failed to learn the task properly and were thus excluded from analysis, rendering N = 43 for this task. Analyses including non-learner participants are reported in the Supplement for thoroughness.

Lexical Trait Judgment Task. To assess self-other similarity judgments between participants and their parents and friends, respectively, we utilized the lexical trait-judgment (LTJT) task (Chavez et al., 2017). On each task trial, participants viewed a trait adjective (e.g., 'Lively') and rated how well it described either themselves, their parent, or their friend (see Figure 1, row C, third schematic). Participants rated ~120 trait adjectives three times each—once on how well it described themselves, another for their parent, and another for their friend—for a total of ~360 ratings. Ratings were made along a four-point Likert scale (1 = "Very uncharacteristic", 4 = "Very characteristic), and trait-individual (e.g., 'Self – Lively') pairings were presented randomly. Importantly, trait adjectives were obtained from a prior study on other-oriented social decision making that used the same parent-friend nomination/salience procedure (described above). That we used traits which individuals from our target population (i.e., a college aged young adult sample, sampled in Guassi Moreira et al., 2018) have previously used to describe their close others is noteworthy because it, in theory, enhances the ecological validity of the task. To avoid valence biases (see Chavez et al., 2017), a third of the selected traits were positively valenced, another third were neutral traits, and the final third were negative traits. To avoid trait-specific effects, two versions of the task with overlapping traits were used (counter balanced across participants, see Supplement). Trait norming procedures are detailed in the Supplement.

Additional Measures. In addition to the computer tasks and self-report measures described here, we also collected data on an additional two computer tasks and several surveys. The computer tasks included a simplified, two-choice version of the SGT and a canonical probabilistic reversal learning task (identical to the one used in Guassi Moreira, Parkinson, & Silvers, 2017). Additional questionnaires tapped cognitive reappraisal capacity, cognitive reappraisal tendency, behavioral suppression tendency, domain-specific risk-taking, sensation-seeking, and perceived stress. These measures, motivations for their collection, and results from their analysis are described at length in the Supplementary Materials. All computer tasks were programmed in PsychoPy (Versions 1.82.01 and 1.84.2; Peirce, 2007), and all self-report instruments were collected on the web-based Qualtrics platform.

Analysis Plan

We divided our statistical approach into two stages. First, we tested whether parent preferences were conserved across three different domains: decision-making under risk (CCT), probabilistic learning (SGT) and self-other similarity judgments (LTJT). This involved computing key metrics from each of the three tasks and submitting them to significance testing. Afterwards, we used random coefficient regression to characterize the extent to which parent—friend preferences differed or remained similar across domains within individuals. The rest of this section is devoted to describing our (i) task-specific parameterizations of parent—friend preferences and how we used them to evaluate group-level trends in said preferences, and (ii) the random coefficient regression framework used to test cross context (task) relationships between parent—friend preferences.

Parent-Friend Preferences in the CCT. Our modeling strategy for the CCT was consistent with prior approaches (see van Duijvenvoorde et al., 2015 and van Duijvenvoorde, Blankenstein, Crone, & Figner, 2017 for an overview). Using a random coefficient regression model, we modeled the trial-by-trial likelihood of turning over a card (1 = turn over, 0 = pass) as a function of an intercept, condition (1 = parent gain/friend lose, 0 = friend gain/parent lose) and basic features of the task (e.g., return (expected value) and risk (outcome variability). All slopes (interception, condition, return, and risk) were allowed to vary randomly across individuals. We first ran a model with only level 1 (within-subject) predictors while allowing slopes to vary randomly between individuals, and then we ran a second model that allowed sex, parent relationship quality, and friend relationship quality to interact with all level 1 slopes (i.e., said between-subject variables predicted all within-subject associations).

Parent-Friend Preferences in the SGT. We extracted estimates of parent—friend preferences during probabilistic learning on the SGT. This involved computing three metrics. Notably, the metrics described here have been used in prior, similar work (e.g., Kwak et al., 2014).

Learning index. A Learning Index (LI) was calculated separately for parents and friends on the SGT task. LIs were defined as the difference in draws from advantageous decks and disadvantageous decks for each close other (LI_{Parent} = [# cards drawn from P+/F+ and P+/F- decks] – [# cards drawn from P-/F+ and P-/F- decks]; LI_{Friend} = [# cards drawn from P+/F+ and P-/F+ decks] – [# cards drawn from P+/F- and P-/F- decks]). LI estimates reflect information about decision outcomes but do not model the mental computations that underlie decision-making.

Alpha parameter. We used a reinforcement learning model on the SGT data to estimate parameters thought to reflect underlying mental processes. The first part of this model gives us our second metric: the α (alpha) parameter, which we refer to as parent—friend reward weighting. In order to conceptualize alpha, we first assume that each participant implicitly or explicitly assigned a subjective value (V_{ij}) to the *i*th deck on the *j*th trial. We modeled said values as:

$$V_{ij} = \alpha Q_{Pij} + (1 - \alpha) Q_{Fij} \quad (1)$$

Here, Q_{Pij} and Q_{Fij} respectively represent the anticipated rewards for one's nominated parent and friend for the *i*th deck on the *j*th trial, and alpha therefore reflects how anticipated rewards for parent and friend are respectively weighted when computing the subjective value one assigns to a deck. Alpha values are bound between zero and one – an alpha of one would mean value is assigned exclusively to anticipated parent outcomes while completely ignoring friend outcomes; an alpha of zero indicates the opposite.

Learning rate. The next part of the reinforcement learning model explains how anticipated rewards for parent and friend are calculated while introducing our third and final metric, learning rates. Learning rates, denoted with λ, come into play when modeling anticipated rewards for parents and friends as a function of the prior trial's anticipated reward (i.e., $j - 1$) and a error:

$$Q_{Pij} = Q_{Pi(j-1)} + \lambda_P(R_{Pj} - Q_{Pi(j-1)}) \qquad (2)$$

$$Q_{Fij} = Q_{Fi(j-1)} + \lambda_F(R_{Fj} – Q_{Fi(j-1)}) \qquad (3)$$

Here, R values indicate actual earned points for parents and friends (specified by the P or F subscripts) on the current trial and λ_P and λ_F weigh prediction errors ($R_j – Q_{i(j-1)}$) when updating anticipated outcomes. Another way of conceptualizing learning rates is that they reflect one's sensitivity to, or willingness to use, feedback. Subjective values (V_{ij}) for each deck were translated into choice probabilities using the softmax equation. This allowed us to estimate parameters by minimizing the negative loglikelihood using the software package R's `optim()` function (starting values for parameter estimates were obtained via grid search).

Summary of SGT metrics. To summarize, *learning indices* tally the number of advantageous choices (i.e., high EV) against disadvantageous choices (i.e., low EV), capturing 'achieved learning' as opposed to directly reflecting information about underlying propensities and computations; the *alpha (α) parameter* reflects the degree to which participants weigh anticipated rewards for parents and friends when computing the subjective value of a given deck; the *learning rate (λ) parameters* describe the extent to which participants use prediction errors to update representations of anticipated rewards (i.e., degree of sensitivity to feedback) for parents and friends.

Parent—Friend Preferences in the LTJT. We leveraged a representational similarity analysis (RSA) framework to compute how similar to parents and friends our participants judged themselves to be. Originally developed for use in systems neuroscience to compare multivariate patterns of brain activation states (Kriegeskorte, 2008), RSA has been increasingly used in psychological science to elegantly compare multidimensional representations of purely behavioral or mental phenomena (e.g., Brooks & Freeman, 2018; Freeman, Stolier, Brooks, Stillerman, & Freeman, 2019). We computed pairwise correlations between (self, parent) and (self, friend) ratings separately across positive, neutral, and negative traits. The impetus for splitting the calculation this way was to avoid artificially inflating self-other similarity judgment values on the basis of rank-order similarity in ratings due to valence. The ensuing three similarity metrics for (self, parent) and (self, friend), respectively, were averaged to yield a single self-other similarity judgment score for each close other (see Figure 2 for an overview).

Comparing Within-Person Consistency in Parent-Friend Preferences. We leveraged random coefficient regression modeling to compare how parent-over-friend preferences during other-oriented decision-making during the CCT track with preferences in the other domains (probabilistic learning, self-concepts). To this end, we employed the same basic modeling framework described for analysis of the CCT while adding metrics of parent-friend preferences as second-level (i.e., between-person) predictors. Our inclination to build upon the CCT model, in particular, was driven by the fact that it was the only existing framework to model competing parent-friend preferences. For thoroughness, we also examined correlations between parent-friend preference metrics from the SGT and LTJT.

Additional Analyses. As noted earlier, we conducted additional analyses to determine whether relationship quality accounted for individual differences in social decision making preferences across domains. Analyses with relationship quality are reported throughout this document. Analyses performed with other questionnaire measures are reported in the Supplement.

Results

Parent—Friend Preferences during Risky Decision Making (CCT). We estimated a logistic random coefficient regression model using the Hierarchical Linear Modeling software (HLM for Windows, Raudenbush & Byrk, 2002) to quantify parent-friend preferences in other-oriented decision making on the CCT. Table 1, Panel A shows that we replicated our prior finding that late adolescents prioritize their parent over their friend during the task (Guassi Moreira et al., 2018). Participants were 35.39% (Odds ratio: $e^{0.303} = 1.3539$) more likely to flip a card in the 'parent gain – friend lose' condition compared to the opposite condition (Fig 3a). When adding relationship quality scores as between-person predictors (i.e., moderators of within-person associations), only perceived relationship quality with friends moderated other-oriented decision-making ($\gamma = -0.253$, $p = .027$)—perceived relationship quality with parents did not ($\gamma = 0.020$, $p > .250$). Thus, individuals with greater perceived relationship quality with friends were relatively more likely to favor friends in the CCT (replicating our earlier work), but no such effect emerged for parents (failing to replicate our earlier work). We replicated a prior effect showing that participants reported higher perceived relationship quality with friends relative to parents (Mean (SD)-Parent: 3.86 (0.62); Mean (SD)-Friend: 4.29 (0.49); $t(45) = -4.609$, $p < .001$, Cohen's $d = -0.680$). We also found an effect of sex, such that female participants were more likely to favor parents over friends than male participants (female participants 45.94% more likely to favor parent over friends, male participants were only 14.80% more likely). This sex moderation is consistent across other models (see Tables 2-4) and was not observed in our prior work (Guassi Moreira et al., 2018).

Parent—Friend Preferences during Probabilistic Learning (SGT). We observed mixed evidenced as to whether participants demonstrated a definitive parent or friend preference during the SGT. A paired-sample t-test revealed significant differences in SGT learning indices for parent and friend (Mean (SD)-LI_P: 30.19 (20.23); Mean (SD)-LI_F: 12.98 (28.12); $t(42) = 3.710$, $p = .001$, Cohen's $d = 0.566$) (Fig 3b), such that participants tended to learn parent-relevant reward contingencies better than friend-relevant contingencies. However, our observed estimate of parent—friend reward weighting (i.e., α parameter from the SGT model) was not significantly different from a null value of 0.50 (Mean (SD)-α: 0.53 (0.27); $t(42) = .169$, $p > .250$, Cohen's $d = 0.111$). Similarly, values in parent and friend learning rates (i.e., λ_P & λ_F parameters from the SGT) did not differ significantly (Mean (SD)-λ_P: 0.47 (0.37); Mean (SD)-λ_F: 0.45 (0.38); $t(42) = .260$, $p > .250$, Cohen's $d = 0.040$). These results suggest that participants learned better for parents relative to friends (learning indices), appeared to weigh parent rewards slightly more than friend rewards (α, parent-friend reward weighting), and seemingly updated anticipated rewards for parents and friends in response to feedback in comparable ways (λ, learning rates).

A larger weighting (α) value (i.e., greater parent preference) was significantly associated with a more unstable (i.e., higher) learning rate for one's friend ($r = 0.59$, $p<.001$, Supplementary Table 3), but was unrelated to parent learning rate. Similarly, a greater α value was directly predictive of a higher learning index for one's parent ($r = 0.36$, $p = .019$, Supplementary Table 3) and unrelated to friend learning index. In terms of associations with subject relationship quality, only friend learning rates were related to friend relationship quality ($r = -.42$, $p = .005$, Supplementary Table 3). Subject-specific plots of parent and friend LI values across time (broken down by blocks; 10 blocks, 15 trials/block) are available on the project's OSF page.

Parent—Friend Preferences in Self-Other Similarity Judgment (LTJT). We found that participants evinced marginally significant higher self-other similarity judgments with their parents in comparison to their friends ($t(45) = 1.906$, $p = .063$, Cohen's $d = 0.281$). However, these findings were no longer marginally significant after removing SGT outliers (Mean (SD)-Parent: 0.30 (0.18); Mean (SD)-Friend: .26 (0.21); $t(42) = 1.653$, $p = .106$, Cohen's $d = 0.252$) (Fig 3c). Despite this, the effect sizes between the two directly aforementioned analyses remained comparable, suggesting that participants evinced a slight parent preference over friends in self-other similarity judgment. Self-similarity overlap with one's parent and friend were strongly related ($r = 0.61$, Supplementary Table 3). Parent relationship quality was directly associated with both self-parent and self-friend similarity ($r = 0.39$, $p = .009$, $r = 0.32$, $p = .034$ respectively), whereas friend relationship quality was only associated with self-friend similarity ($r = .45$, $p = .003$) (Supplementary Table 3).

Cross-Domain Comparisons of Parent—Friend Preferences. The results of the parent-friend cross-domain comparisons are fully outlined in Tables 2-4 and visualized in Figure 4.

With respect to relationships between the CCT (risk-taking) and SGT (probabilistic learning), we found a higher friend learning index (greater LI_F value) on the SGT was related with relatively greater friend preference on the CCT (Table 2; $\gamma = -0.005$, $p = .002$) whereas a greater parent learning index was initially not related preferences on the CCT (Table 2; $\gamma = 0.002$, $p = .225$). Next we observed that individuals with greater parent-reward weighting (i.e., greater α value) on the SGT tended to favor their parents over their friends on the CCT (Table 3; $\gamma = 0.313$, $p = .042$). Last, a more stable parent learning rate (lower λ_P value) on the SGT was related to more exaggerated parent preferences on the CCT, whereas a more stable friend learning rate (lower λ_F value) was related to marginally more pronounced friend preference on the CCT (Supplementary Table 1). Afterwards, we removed non-learners—outliers who did not learn the task properly (Kwak et al., 2014)—and re-ran our analyses. This step is important because the reinforcement learning model we fit assumes that agents are actively learning during the task, and indices extracted from non-learners are thus difficult to interpret. We found (i) the effect of friend learning index on CCT preferences remained significant (Supplementary Table 7; $\gamma = -.008$, $p = .001$) whereas the effect of parent learning index on CCT preferences became marginally significant (Supplementary Table 7; $\gamma = .004$, $p = .094$), (ii) the effect of parent-friend weighting on CCT preferences remained comparable to before but dropped out of marginal significance (Supplementary Table 5; $\gamma = .252$, $p = .131$), and (iii) the effect of friend learning rate on CCT preference dropped out of marginal significance (Supplementary Table 1; $\gamma = -.105$, $p = .393$) whereas the effect of parent learning rate on CCT preferences remained significant (Supplementary Table 1; $\gamma = -.452$, $p = .001$). From these data we conclude that there are moderate to strong relationships between social decision making preferences in the risk taking and probabilistic learning domains.

Curiously, greater levels of self-other similarity on the LTJT (self-other similarity judgment) with one's parent and friend resulted in a *reduced* tendency to favor them on the CCT. That is, greater self-parent similarity judgment was inversely associated with reduced parental preference on the CCT ($\gamma = -1.049$, $p = .002$), and greater self-friend similarity judgment was marginally linked with reduced friend preference on the CCT ($\gamma = 0.547$, $p = .076$) (Table 4).

Last, bivariate Pearson's correlations between metrics of parent-friend preference on the SGT and the LTJT showed no strong, systematic relationships (statistics reported in

Supplementary Table 3). The only statistically significant association present was, counterintuitively, a direct relationship between self-friend similarity overlap and parent learning index (r = 0.32, p<.039 excluding learning index outliers; r = 0.10, p>.250 including outliers).

Study 2.

Study 2 was conducted as a confirmatory effort to replicate the findings from Study 1 in a larger, independent sample. The *a priori* hypotheses for this study can be found on the OSF (osf.io/6278m). Hypotheses centered on replicating parent-over-friend within-task effects and again testing cross-domain consistency between social decision making preferences. Pre-registered hypotheses can be viewed online (osf.io/6278m), and are also re-printed in the supplement for convenience.

Methods

Participants. Participants in Study 2 were also recruited from the University of California, Los Angeles' undergraduate psychology subject pool. Participants were initially recruited between the months of August, 2018 and March, 2019, and again between May-July 2019, as part of a broader, pre-registered effort aimed at collecting data about social decision making preferences in close others (osf.io/6278m). In order to participate, individuals were required to be between the ages of 18 and 30 and must not have previously participated in Study 1. Sample sizes were set *a priori* for a number of social decision making tasks at N = 225 each—participants were assigned to complete unique combinations of two tasks, resulting in cross-task cells of n = 75. This additional data collection period yielded a total sample size of 600 for Study 2 (448 female, Mean age = 20.47, SD = 1.71), collapsed across the three tasks. Ethnically, 21% of participants identified as Hispanic/Latinx. Racially, 43% identified as Asian, 28% identified as White, 3%

identified as African American, 0.5% identified as Native Hawaiian/Pacific Islander, 0.5% identified as American Indian/Alaska Native, 12% identified as Other, 7% identified as Mixed Race, and 6% refused to respond. All participants were compensated with course credit and provided written consent as in Study 1. All data and materials for Study 2 are available on the OSF (osf.io/d42ar). More information about the two data collection efforts that comprised Study 2 are available in the Supplement under “Study 2 – Hypotheses & Additional Data Collection Details.”

Procedure

Study 2’s procedure was highly similar to Study 1. The chief difference this time was that most participants were assigned to complete just two social decision making tasks (as opposed to several, in Study 1).

Measures

All tasks and self-report measures in Study 2 were identical to those in Study 1. Additional data were collected in Study 2 that are outside the scope of this manuscript and results are thus not reported here. A full list of measures is available with Study 2’s pre-registration (osf.io/6278m).

Analysis Plan

Data from Study 2 were processed and analyzed in the same manner as in Study 1. The same processing, and computational and statistical models/tests were used. A summary of the statistical significance of key research questions broken down by study is included in Table 5 for convenience.

Results

Parent—Friend Preferences during Risky Decision Making (CCT). We first ran the within person (Level 1, unconstrained) model and successfully replicated the results of Study 1: Participants were 19.92% more likely to favor their parent over their friend ($\gamma = 0.182$, SE = .034, $p < .001$), and we also observed similar effects of return and risk on decision making (return: $\gamma = 0.034$, SE = .002, $p < .001$; risk: $\gamma = -0.046$, SE = .002, $p < .001$). Results from our full model are provided in Table 1, Panel C. Notably, we replicated our prior finding that relationship quality with friends and parents moderated preferences such that greater relationship quality with parents was related with greater preferences for parents ($\gamma = 0.200$, SE = .041, $p < .001$) and greater relationship quality with friends was related with greater preferences friends ($\gamma = -0.284$, SE = .094, $p = .003$). Last, the sex differences on social decision making preferences observed in Study did not replicate ($\gamma = 0.055$, SE = .075, $p > .250$).

Parent—Friend Preferences during Probabilistic Learning (SGT). We first began by evaluating parent and friend learning indices. We again found significant differences between parent and friend, in the same direction (i.e., parent preference) as Study 1 (Mean (SD)-LI_P: 26.67 (26.81); Mean (SD)-LI_F: 14.47 (29.58); $t(222) = 5.756$, $p < .001$, Cohen's $d = 0.385$). Notably, the effect size for this test is noticeably smaller than in the first study ($d = 0.385$ compared to $d = .566$). We then turned our attention towards our new estimate of parent-friend reward weighting (α). Though the mean value of this parameter—and its accompanying effect size—is comparable to Study 1, the effect is now marginally significant from a null value of 0.50 in Study 2 ($N = 223$, Mean(SD)-α: 0.54, (0.31); $t(222) = 1.839$, $p = .067$, Cohen's $d = .123$). Finally, we replicated the null (i.e., non-significance) difference in parent and friend learning rates (i.e., λ_P & λ_F parameters) that was observed in Study 1 (Mean (SD)-λ_P: 0.34 (0.36); Mean (SD)-λ_F: 0.36 (0.38); $t(222) = -.392$, $p > .250$, Cohen's $d = -0.026$).

As in Study 1, we re-ran analyses excluding outliers (e.g., individuals who did not learn the task appropriately). We found (i) the paired differences in parent-friend learning indices remained significant (Mean (SD)-LI_P: 41.78 (27.45); Mean (SD)-LI_F: 26.50 (33.84); $t(108) = 3.817$, $p < .001$, Cohen's $d = 0.366$), (ii) our parent—friend weighting parameter (α) evinced a similar effect size as before (albeit was no longer marginally significant; N = 109, Mean(SD)-α: 0.54, (0.25); $t(109) = 1.525$, $p = .130$, Cohen's $d = .146$), and (iii) the paired differences in parent-friend learning rates were not significant (Mean (SD)-λ_P: 0.41 (0.35); Mean (SD)-λ_F: 0.46 (0.38); $t(108) = -1.196$, $p = .234$, Cohen's $d = -0.115$). These results lend themselves to the same conclusion as in Study 1: Participants learn parent-relevant reward contingencies better than friend-relevant contingencies, tend to weigh rewards for parents slightly (given our effect size, but not significantly) more than for friends, but appear to be equally sensitive to parent and friend feedback.

Parent—Friend Preferences in Self-Other Similarity Judgment (LTJT). We failed to replicate the findings from Study 1 in Study 2, and did not observe any evidence that self-similarity overlap was greater with participant's parents compared with friends. There was insufficient evidence to reject the null hypothesis that the mean paired difference between self-parent and self-friend similarity values is zero ($N = 223$, Mean (SD)-Parent: 0.721 (0.13); Mean (SD)-Friend: .712 (0.14); $t(222) = 0.857$, $p > .250$, Cohen's $d = 0.057$). Analyses excluding subjects with many missing responses are described in the Supplement, but our results remain unchanged. Self-similarity overlap with one's parent and friend were once again related, albeit not as strongly as before ($r = 0.36$ ($p < .001$), compared to 0.61 in Study 1).

Cross-Domain Comparisons of Parent—Friend Preferences.

As in Study 1, we ran a series of models to examine whether individual differences in parent-friend preferences were consistent across domains.

Risk Taking and Probabilistic Learning. We replicated our prior finding that learning indices for parent on the SGT were predictive of a marginally greater tendency to favor parents on the CCT (Table 2, Panel B; $\gamma = .009$, $p = .052$) and friend learning indices on the SGT were associated with a significantly greater tendency to favor friends on the CCT (Table 2; $\gamma = -.009$, $p = .018$). Like Study 1, we assessed whether parent-friend reward weighting values (α) on the SGT (assessing probabilistic learning) predicted parent-friend preferences on the CCT (assessing risk taking). The effect size for this analysis in Study 2 was comparable to Study 1, but unlike Study 1, was not significant (Table 3; $\gamma = .295$, $p = .176$). Last, learning rates for parents and friends on the SGT were not predictive of behavior on the CCT (Supplementary Table 6). Overall, these results largely replicate the findings from Study 1 that showed social decision making preferences across the probabilistic learning and risk taking domains corresponded within individuals.

Non-learning outliers were then excluded and analyses were re-run ($N = 41$). These results showed (i) the effect of parent and friend learning indices on CCT preferences remained significant or marginally significant (Supplementary Table 7; Parent $\gamma = .009$, $p = .052$; Friend $\gamma = -.009$, $p = .018$), (ii) the effect of parent-friend reward weighing values on the CCT became marginally significant (Supplementary Table 5; $\gamma = .908$, $p = .069$), and (iii) the effect of parent learning rate on CCT behavior remained non-significant (Supplementary Table 6) and the effect of friend learning rate on CCT behavior became significant (Supplementary Table 6; $\gamma = -.232$, $p = .024$) such that individuals with more volatile learning rates for friends tended to favor their friends on the CCT.

Risk Taking and Self-Other Similarity Judgments. There were no systematic relationships between parent-friend self-other similarity judgments on the LTJT and social decision making preferences during risk taking on the CCT (Table 4).

Probabilistic Learning and Self-Other Similarity Judgments. Like Study 1, parent-friend preference on the SGT and the LTJT showed no strong, systematic relationships. The lone significant association between the SGT and LTJT from Study 1 (between self-friend similarity overlap and parent learning index) did not replicate this time (r = .12, p > .250).

Discussion

Human beings routinely make decisions across varied contexts that affect those close to them. Despite recent progress in social decision making research, virtually no prior studies had examined whether social decision making preferences between close others are consistent across contexts and within individuals. Here, we (i) replicated our prior work demonstrating that young adults display a preference for their parents over friends when making risky decisions, (ii) found exploratory and confirmatory evidence that this parent-over-friend preference generalizes to some aspects of probabilistic learning but not self-other similarity judgment domains, and (iii) showed that individual differences in the probabilistic learning domain tracked with individual differences in the risk taking domain whereas individual differences in self-other similarity judgments tracked with neither. In all, these results suggest that preferences are conserved when making social decisions that involve risk and probabilistic learning, but not those that involve self-other similarity judgments.

Successful Replication of Parent-Oriented Preferences in the Risk-Taking Domain. The first notable result from this study was the successful replication of Guassi Moreira and colleague's recent findings (2018) showing that young adults are more likely to prioritize their parents over friends when making decisions in the risk taking domain. This replication instills confidence in the reported effects in two ways. First, recent high profile failures to replicate seminal psychological findings (Bouwmeester et al., 2017; Hagger et al., 2016; McCarthy et al., 2018) have reinforced the notion that replication is an integral feature of science and that research findings must not only be judged on their initial impact, but also by their ability to endure further empirical scrutiny (Open Science Collaboration, 2015). Second, our replication efforts help enhance confidence that effect sizes for social preferences (i.e., parent-over-peer preference) have been accurately estimated. In other words, this replication helps solidify our understanding of *how much* individuals favor parents over peers, consistent with growing calls for greater quantitative precision via evaluation of effect sizes. This carries utility for a number of purposes that range from building more precise theories and models, to informing future interventions that seek to capitalize on parental influence.

Parent-Oriented Preferences Generalize to the Probabilistic Learning Domain. Individuals in our sample exhibited a preference in learned outcomes for parent relative to friend in the probabilistic learning domain, but were not strongly biased towards one or the other in terms of the underlying computations that supported learning. While participants were more likely to learn reward contingencies better for their parents compared to friends, participants appeared to weigh anticipated rewards for parents only slightly more than friends (alpha values equal approximately to .52, constituting a small effect size of approximately ~.12) and were equally sensitive in adjusting anticipated rewards for parents and friends based on feedback (paired differences between learning rates were roughly equal to zero). These patterns suggest that social decisions affecting parents and friends may not be driven by different hypothetical payouts for parents or friends (weighting parameter), but are instead dictated by other motivations (Kwak et al., 2014). Learning of this kind is often interpreted as individuals making decisions that satisfy a subjective utility function with respect to goals (Becker, 1976; Smith, 1982), ensuring that individuals attend to and act upon information that is most relevant to maximizing said function. The fact that learning was enhanced when parents stood to gain as opposed to peers suggests that learning on behalf of parents fulfills a *socioemotional* goal for young adults, as opposed to one driven purely by tangible or material outcomes. Developmental psychology research frequently shows that young adults feel a sense of obligation towards, and a need to contribute to, their families (Fuligni, 2018). Thus, one interpretation of our results is that individuals can value close others equitably and be cognizant of changes across competing reward contingencies, while still behaving in accordance to perceived social obligations. The combined use of behavioral modeling (e.g., using reinforcement learning to derive parent-friend value weighting parameters and learning rates based on feedback sensitivity) with traditional metrics of behavior (e.g., parent-friend learning indices based on choice behavior) suggest parent preferences are not merely due to an inability to weigh rewards or respond to feedback on behalf of friends. Instead, the present results suggest that young adults process rewards and feedback to a similar extent for parents and friends but use this information in different ways during decision making. These findings beget new hypotheses for research examining social decision making preferences for parents and friends in other contexts, as well as continue to highlight the importance of searching for additional variables to explain social decision making preferences (e.g., family obligation).

Parent-Oriented Preferences May Not Generalize to the Self-Other Similarity Judgment Domain. Using subject-specific metrics of self-other similarity judgments, we initially found that individuals tended to show slightly greater overlap in representations of themselves and their parent, relative to themselves and their friend. However, our confirmatory results in Study 2 failed to replicate these findings, showing that levels of self-other overlap were comparable for parents and friends. These results have several potential interpretations and implications for social decision making. First, judgments of similarity between oneself and others may be comparable among a range of close others, with larger differences in self-other similarity resulting from comparisons between close others and distant others such as strangers, acquaintances, or celebrities. While we could not test this possibility in the present study because its primary goal was to examine social preferences for multiple close others, this remains an important question for future work. Second, although we did not observe increased average levels of self-other overlap for one close individual over another, it is possible self-other overlap between parents and friends differs across varying semantic domains. For example, a friend might be seen as more similar to oneself in traits related to social behavior (e.g., ‘outgoing’) while a parent might be rated more similar for traits that are related to occupational behaviors (e.g., ‘industrious’). Results from human neuroimaging suggests that the mind encodes information about social stimuli across a vast semantic space (Huth, Heer, Griffiths, Theunissen, & Gallant, 2016; Huth, Nishimoto, Vu, & Gallant, 2012). At the mean level, it is possible that self-other similarity judgments are comparable between parents and friends, but differences might emerge if one were to precisely map out self-similarity at all corners of said semantic space. Last, it is plausible that individuals judge similarities between themselves and others in ways that are not necessarily trait-based, perhaps instead leaning on others’ preferences and actions to determine similarity. Though these possibilities are speculative at this stage of research, they illustrate how the present results may be generative in guiding future research on social preferences and decision making.

Social Decision Making Preferences Track Across Some, But Not All Domains. We found mixed evidence about whether individual differences in social decision making preferences were consistent across the three domains studied here. First, we found that all metrics of preference in the probabilistic learning domain—to varying degrees of consistency—tracked with preferences in the risk taking domain. Though we failed to observe group-level preferences for parent over friend with regards to reward weighting values and learning rates in the probabilistic learning domain, these metrics—along with parent and friend learning indices—still appear to meaningfully encode information about preferences when analyzed in conjunction with data from the risk-taking domain. With that said, we note there was greater inconsistency in whether learning rates in probabilistic learning are predictive of other-oriented risk taking. One reason for this may be due to the modeling strategy. Our reinforcement learning model assumes learning for at least one close other—if a participant does not learn the task at all, the learning rate metrics may be unreliable (Kwak et al., 2014). However, it is difficult to tell if differences in learning rate results including and excluding non-learners is due to this fact or chance. Future work is needed to help verify. That we observed more consistent parent-over-friend preferences at the group-level in the risk taking domain compared to the probabilistic learning domain suggests that there may be hidden moderators at the individual level (e.g., cognitive ability, reward sensitivity) that simultaneously explain between-domain variability and weaken group effects.

Second, we found that self-other similarity judgment values did not reliably track with risk taking behavior nor with any probabilistic learning metrics. One potential explanation for this result is that the preferences we observed in the other tasks may only be relevant for self-other similarity judgments if the traits being assessed were semantically comparable to information encoded in the CCT and SGT. Many of the traits in the LTJT had nothing to do with semantic knowledge related to risk taking or probabilistic learning and thus self-other overlap in those traits perhaps do not have a reason to be correlated with preferences in those other domains. Another explanation is that our measurement of self-other similarity was inaccurate, and that the traits we selected were somehow antithetical to how individuals truly choose to define themselves and others. Though this possibility seems unlikely since these traits were generated by members of the target population (e.g., late adolescents/young adults), it still merits consideration.

If one were to taxonomize psychological processes between the three domains studied here (Eisenberg et al., 2018), it would appear that risk taking and probabilistic learning tap a common, underlying psychological substrate whereas self-other similarity judgments do not. The fact that social decision making preferences correspond between risk taking and probabilistic learning processes, but not self-other similarity judgments, implies that the affective and cognitive underpinnings of the former two are more similar than the latter. This suggests that probabilistic learning and risk taking behaviors, at least as they apply to social decision making, rely on similar psychological mechanisms. Perhaps they enjoy mutual links because they both rely on computations of socially-derived rewards, a possibility that is in line with theoretical accounts that highlight the role of reward processes in social motivation (Pfeifer & Berkman, 2018; Wake & Izuma, 2017). By contrast, self-other similarity judgments may depend less on value or reward computations and instead engage higher-order social cognitive mechanisms to drive decisions. The present data thus suggest that social decision making processes ought to be categorized according to discrete, supraordinate domains – for example, those that rely upon value-based versus social cognitive computations. In considering this issue, we note that simply because similar preferences emerged across value-based domains does not mean that the mechanisms or computations within each domain are identical. Valuation of parent versus friend outcomes may operate differently in risk taking and probabilistic learning contexts, and depend on other situation features not considered here. Therefore, while we find the notion of supraordinate, domain-specific computations enticing, we recognize more work is needed to characterize underlying computations.

Limitations & Future Directions. The present study is subject to a number of limitations. A few limitations are related to the exploratory nature of the research. First, although we collected data in a large number of participants (46 in Study 1; 600 in Study 2), our use of a partially between-subject task design (chosen to reduce the possibility of participant fatigue) yielded more modest sample sizes for cross-domain comparisons when compared to other social decision making studies (FeldmanHall et al., 2012; Seaman et al., 2016). Another potential limitation concerns our lack of a 'self' condition in the risk taking and probabilistic learning tasks. That is, it was unclear how individuals prioritize between multiple close others compared to themselves. This is noteworthy to mention because some individuals may have viewed one of the two close others as being included as part of the self. In this case they would not have been prioritizing one person other over the other, but instead prioritizing themselves—through one close other—over another (Sparks, Cunningham, & Kritikos, 2016). Although our data from the LTJT—which show comparable levels of self-other overlap between parents and friends—suggest this is unlikely, this is nevertheless worth considering in future research. One final limitation concerns constraints on the generalizability of our results, such as regional/state differences in qualitative aspects of close relationships, cultural differences among different genders and ethnic groups, economic climate, and potential age differences. However, we note that age differences in effects, in particular, actually represent an exciting avenue for future research since young children, adolescents, young and middle-aged adults each have qualitatively different social relationships and goals for such.

Future work might also benefit from examining parent-friend preferences in other decision making domains (e.g., discounting), measuring whether the same preferences emerge for other reward types (e.g., monetary vs social rewards), and determining what cognitive processes (e.g., loss or risk aversion) support social decision making preferences. Other follow-up work could better seek to better understand the role that relationship-level features (e.g., perceived obligation to one’s parent or friend) play in shaping social decision making preferences. Further still, additional follow-up work is needed to disentangle cultural differences in social decision making preferences involving close others. Indeed, there are well documented cultural differences in how stimuli are defined in relation to the self and others (Sparks, Cunningham, & Kritikos, 2016). Though our data were not properly equipped to address cultural dynamics resting along dimensions such as collectivism—individualism, we believe a fundamental understanding of social decision making will not be achieved until such issues have been appropriately addressed.

Conclusions. These paired exploratory and confirmatory studies examined how social decision making preferences generalize across domains. Our findings show that social decision making preferences are translatable between certain domains (risk taking and probabilistic learning), but not others (self-other similarity judgments). Substantively, these results also speak to the continued importance of parent relationships during young adulthood. The findings here lay the groundwork for additional, confirmatory work that will help expand and further enrich psychological science's knowledge of how decision making and social relationships mutually influence one another.

Context of the Research. While focused on young adults, the current report owes its roots to adolescent psychology research. It had long been noted that adolescents tend to engage in different degrees of risky behavior across varying social contexts – for example, when they are with their parents versus their friends. A separate line of research has recently begun to examine not only how adolescents and young adults make risky decisions that impact themselves, but also for other people. However, most other-oriented decision making research to date has been focused on making decisions for strangers, rather than the people closest to us. In noting this, we became interested in how young people make decisions that stand to impact close others. We found in a prior study that young adults seemed to prioritize their parents over their friends when making decisions, but that result was observed with just one decision making task. In the present study, we thought it was important to determine whether social decision making preferences involving close others are preserved across decision making contexts. Our future research will seek to examine similar social preferences in young adolescents, as well as to uncover the neural mechanisms that drive these preferences.

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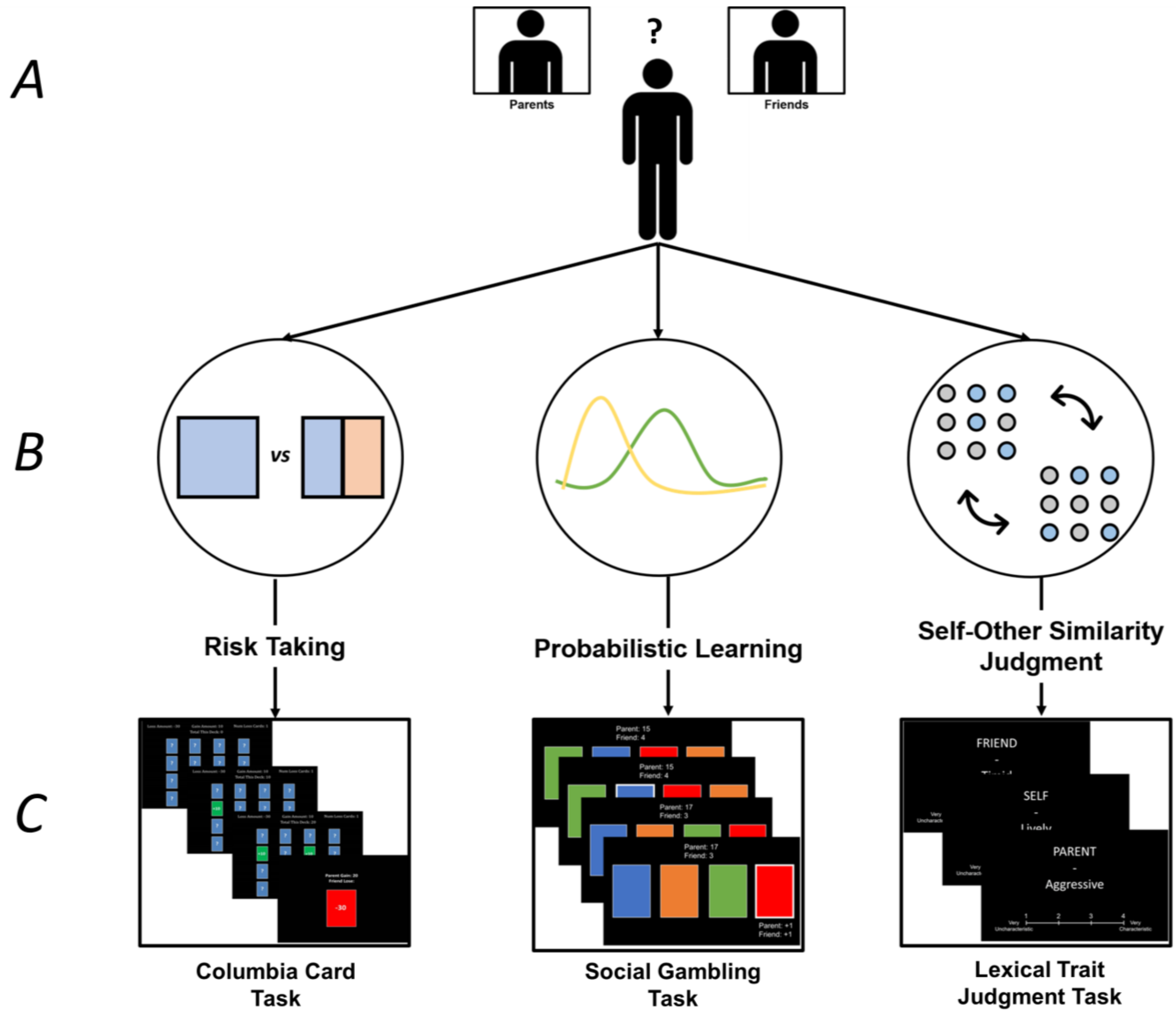
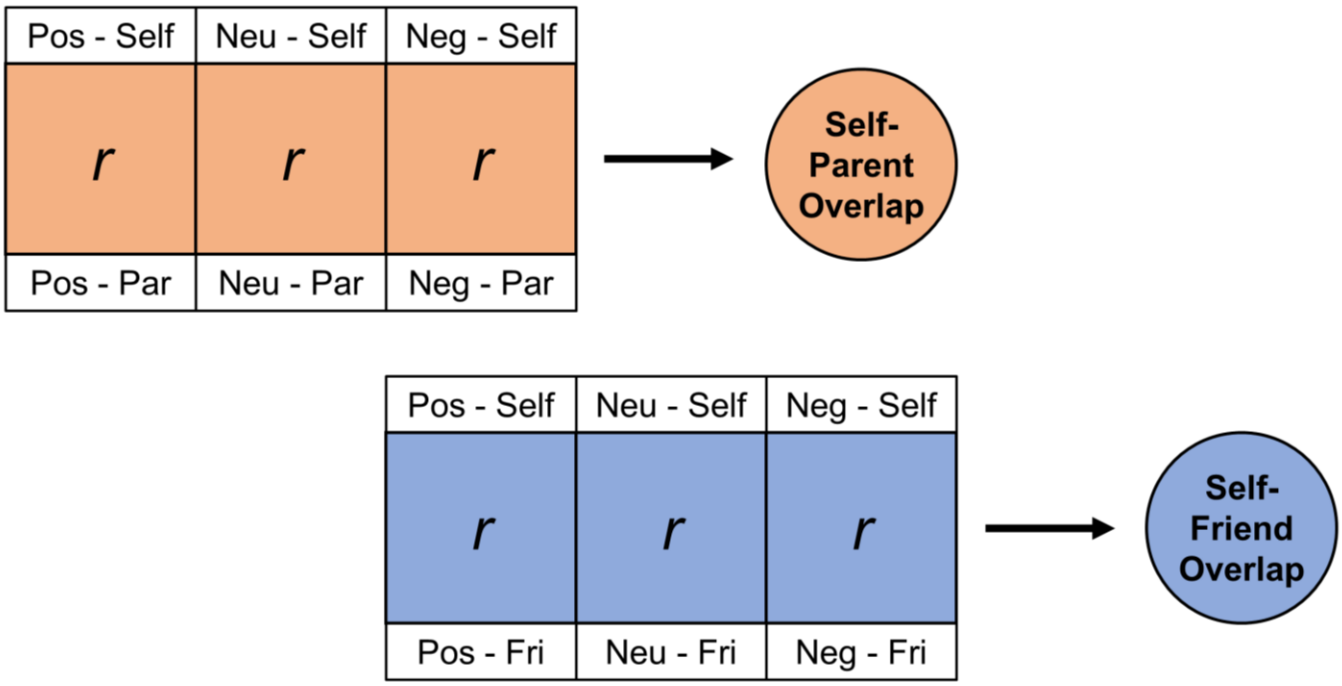
Figure 1. Overview of social decision making domains studied and their respective experimental tasks.



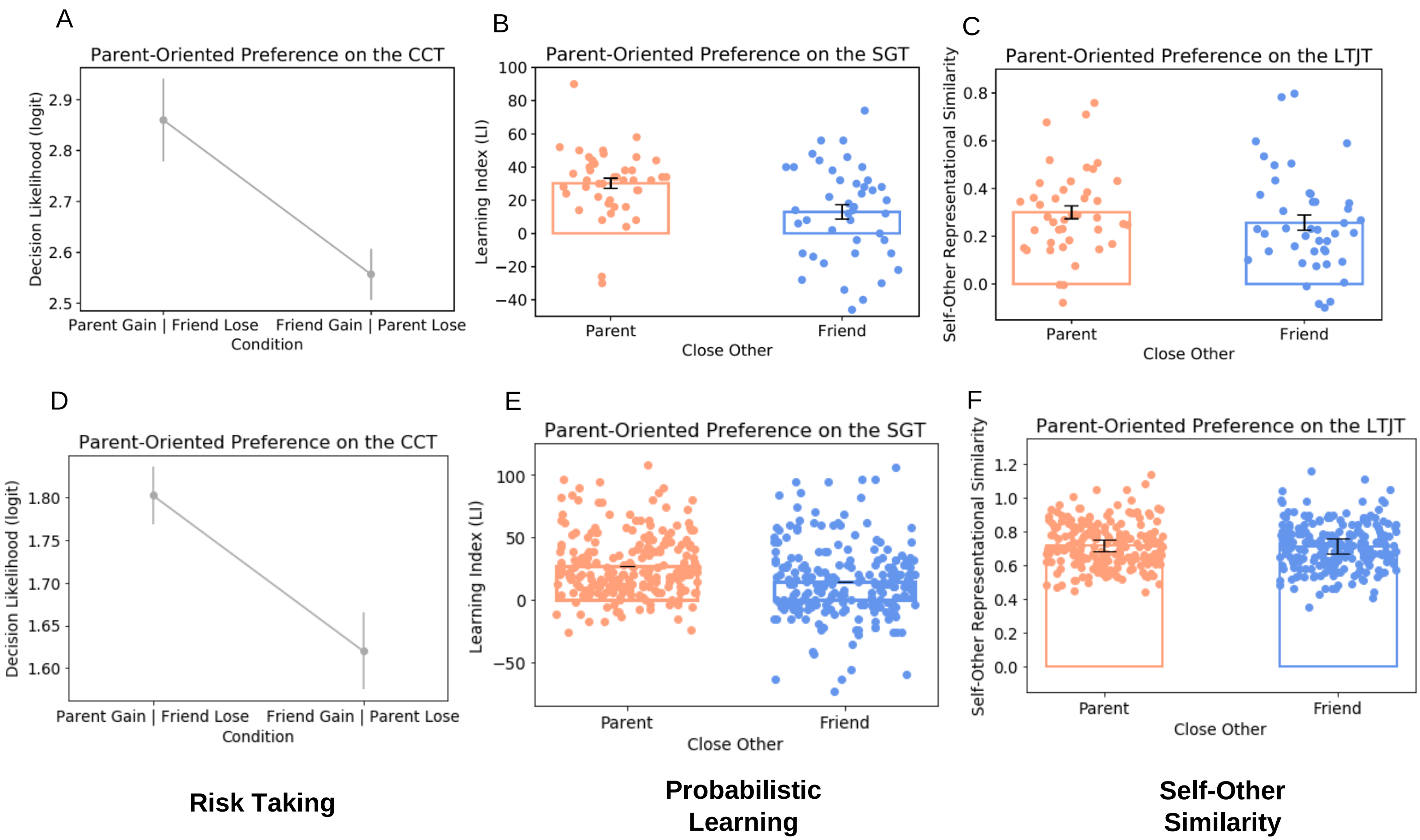
Note. Row A depicts that individuals must navigate social decision making tradeoffs. Tradeoffs can occur across a variety of social decision making domains, schematized in row B. The first schematic bubble represents the risk taking domain, the second schematic bubble represents the probabilistic learning domain, and the third schematic bubbles symbolizes the self-other similarity judgment domain. The tasks we used to model social decision making preferences in these domains are shown in Row C. The Columbia Card Task (CCT) is shown first, the Social Gambling Task (SGT) is second, and the Lexical Trait Judgment Task (LTJT) shown last in the row.

Figure 2. Conceptual overview of representational similarity analysis used to assess self-other similarity judgments for parent and friend on the Lexical Trait Judgment Task



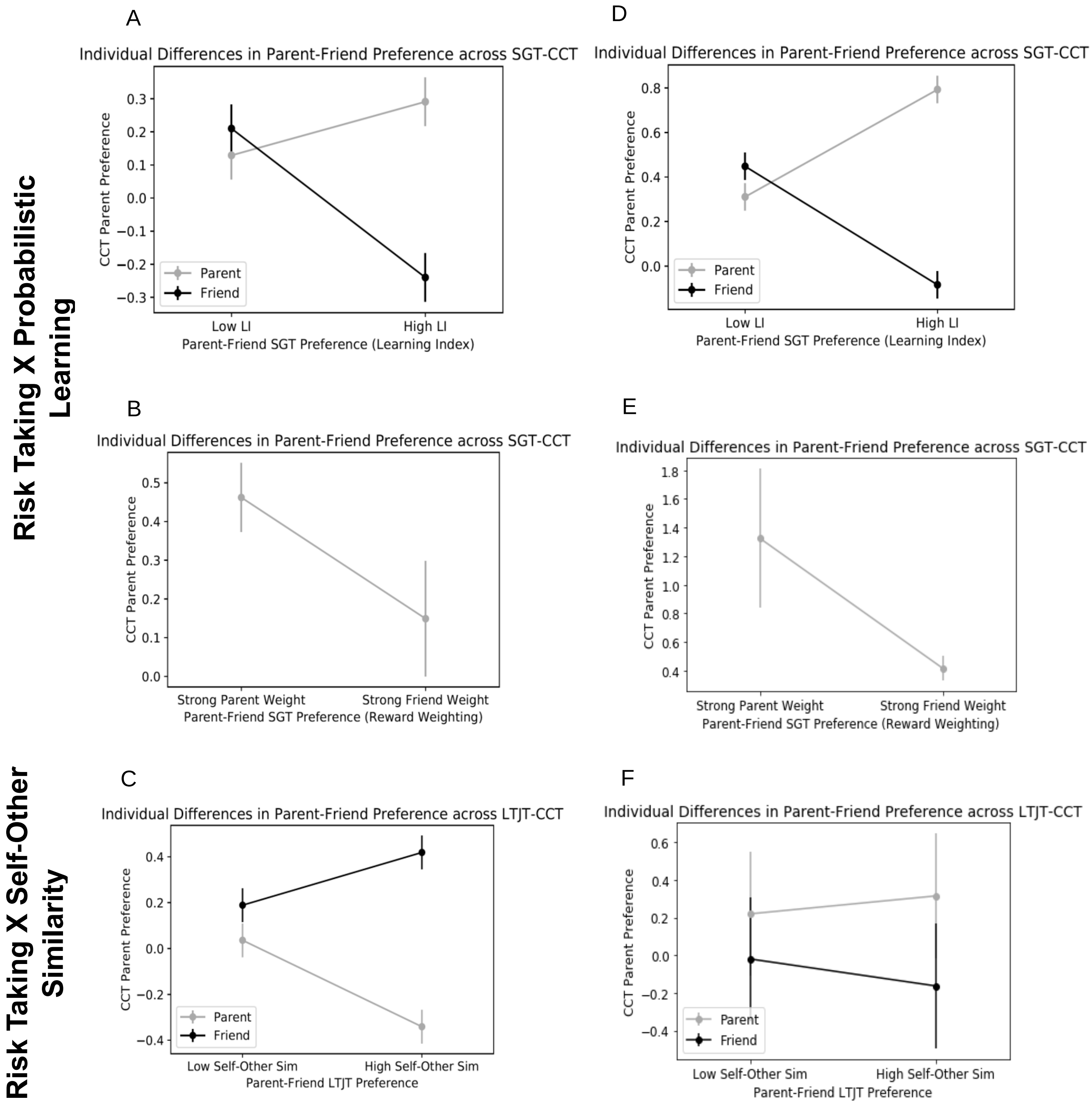
Note. 'Pos' refers to positively valenced traits, 'Neg' refers to negatively valenced traits, and 'Neu' refers to neutrally valenced traits; 'Par' refers to parent, and 'Fri' refers to friend. Boxes with '*r*' denote correlation between ratings of self and close other (parent or friend) for traits of a given valence. Correlations were averaged to yield a single metric of Self-Other representational overlap for parents and friends.

Figure 3. Parent preference is conserved across performance during risk taking (a; CCT) and probabilistic learning (b; SGT), but inconsistently for self-other similarity judgments (c; LTJT,) in Studies 1 and 2. Study 1: A-C; Study 2: D-F



Note. (a,d) ‘Decision Likelihood’ refers to the likelihood (in logits) of choosing to flip over a card on the risk taking task (CCT) as a function of condition in Study 1 and Study 2. Condition refers to whether decisions benefited a parent at the potential expense of a friend or vice versa. Values reflect fixed-effect coefficients of our random coefficient regression model of CCT data; error bars indicate +/- 1 standard error of the parameter estimates. (b,e) Learning Index refers to number of advantageous minus disadvantageous decisions made for each close other on the probabilistic learning task (SGT) in Study 1 and Study 2. Error bars indicate +/- 1 standard error of the mean. (c,f) Self-Other Representational Similarity Refers to values taken from RSA analysis of the LTJT (self-other similarity judgment) in Study 1 and Study 2. Error bars indicate +/- 1 standard error of the mean.

Figure 4. Parent-Friend Preferences in the SGT (probabilistic learning task) and LTJT (self-other representational similarity task) are Systematically Related to Parent-Friend Preferences on the CCT (risk taking domain) in Study 1 (A-C) and Study 2 (D-F).



Note. (a,d) depicts relationships between individual differences in SGT learning rates (LI) and CCT preference in Study 1 and Study 2. Ticks on the X-axis indicate LIs +/- 1SD above/below average. (b,e) depicts relationships between individual differences in SGT parent-friend reward weighting (α) parameters and CCT preference in Study 1 and Study 2. Ticks on the X-axis indicate complete friend weighting (α=0) and complete parent weighting (α=1). (c,f) depicts relationships between individual differences in self-other similarity judgment on the LTJT and CCT preference in Study 1 and Study 2. The Y-axis on all plot indicates level of parent-friend preference on the CCT; negative values indicate friend preference, positive values indicate parent preference, a value of zero indicates no preference. Analyses involving learning indices and parent-friend reward weighting were significant; Study 1 LTJT analyses (c) were significant/marginally significant but were not significant in Study 2 (f). See tables and text for more information regarding significance.

Table 1. Level 1 Model Predicting Trial-by-Trial Decision-Making on the CCT (risk taking task). Panel A contains the unconstrained Level 1 model (no between-person predictors) from Study 1; Panel B includes additional moderators from Study 1; Panel C is a replication of the full model in Study 2.

Predictor	*A*			*B*			*C*		
	γ	SE	*p*	γ	SE	*p*	γ	SE	*p*
Intercept									
Intercept	2.557	.081	<.001	2.766	.118	<.001	1.620	.106	<.001
Sex	-	-	-	-0.223	.154	.157	0.003	.114	.980
Parent RQ	-	-	-	0.423	.129	.002	-0.085	.082	.298
Friend RQ	-	-	-	-0.380	.138	.009	-0.009	.118	.940
Condition									
Intercept	0.303	.050	<.001	0.138	.089	.133	0.149	.067	.028
Sex	-	-	-	0.240	.108	.031	0.055	.075	.460
Parent RQ	-	-	-	0.020	.067	.761	0.200	.041	<.001
Friend RQ	-	-	-	-0.253	.110	.027	-0.284	.094	.003
Return									
Intercept	0.052	.004	<.001	0.082	.010	<.001	0.038	.003	<.001
Sex	-	-	-	-0.044	.011	<.001	-0.005	.004	.256
Parent RQ	-	-	-	-0.018	.008	.033	-0.001	.003	.777
Friend RQ	-	-	-	0.018	.009	.054	-0.006	.004	.139
Risk									
Intercept	-0.059	.003	<.001	-0.074	.008	<.001	-0.045	.003	<.001
Sex	-	-	-	0.018	.009	.049	-0.002	.004	.642
Parent RQ	-	-	-	-0.005	.006	.430	-0.001	.002	.606
Friend RQ	-	-	-	0.004	.007	.594	-0.003	.003	.431

Note. Condition was coded such that a 0 = friend gain/parent lose, 1 = parent gain/friend lose. Return (EV) ranged from -60 to 16.88 and SD ranged from 9.68 to 40. γ-s are fixed effects and represent expected changes in log odds. Robust standard errors are reported from a population-average model. RQ refers to relationship quality. Sex was coded 0 = male; 1 = female. Panels A & B $N = 45$, Panel C $N = 223$. The unconstrained model from Study 2 is reported in the text.

Table 2. Learning indices (SGT, probabilistic learning task) as moderators of other-oriented decision-making on the CCT (risk taking task). Panel A contains results from Study 1, Panel B contains results from a replication in Study 2.

Predictor	A			B		
	γ	SE	*p*	γ	SE	*p*
Intercept						
Intercept	2.829	.135	<.001	1.792	.141	<.001
Sex	-0.296	.165	.081	-0.340	.188	.078
LI-Parent	0.005	.004	.263	-0.008	.006	.185
LI-Friend	0.003	.003	.371	0.008	.005	.074
Condition						
Intercept	0.089	.073	.230	0.312	.061	<.001
Sex	0.216	.095	.028	0.074	.083	.380
LI-Parent	0.004	.002	.094	0.009	.004	.052
LI-Friend	-0.008	.002	.001	-0.009	.004	.018
Return						
Intercept	0.081	.009	<.001	0.052	.006	<.001
Sex	-0.039	.011	.001	-0.025	.008	.003
LI-Parent	-0.001	.000	.050	0.000	.000	.689
LI-Friend	0.004	.000	.007	0.000	.000	.654
Risk						
Intercept	-0.074	.007	<.001	-0.064	.009	<.001
Sex	0.018	.008	.039	0.010	.010	.296
LI-Parent	-0.000	.000	.255	-0.000	.000	.078
LI-Friend	-0.000	.000	.729	0.000	.000	.822

Note. Condition was coded such that a 0 = friend gain/parent lose, 1 = parent gain/friend lose. Return (EV) ranged from -60 to 16.88 and SD ranged from 9.68 to 40. γ-s are fixed effects and represent expected changes in log odds. Robust standard errors are reported from a population-average model. LI refers to the learning index metric from the reinforcement learning model fit to the SGT. Sex was coded 0 = male; 1 = female. N = 43 for Panel A results. N = 223 for Panel B

Table 3. Alpha values (SGT, probabilistic learning task) as moderators of social decision making preferences on the CCT (risk taking task). Panel A contains results of a Study 1, Panel B contains results from a replication of Study 2.

Predictor	A			B		
	γ	SE	*p*	γ	SE	*p*
Intercept						
Intercept	2.761	.141	<.001	1.675	0.109	<.001
Sex	-0.263	.173	.136	-0.062	0.146	.671
α (SGT)	-0.004	.315	.991	0.053	0.268	.843
Condition						
Intercept	0.149	.089	.102	0.302	.085	.001
Sex	0.200	.108	.070	0.081	.106	.450
α (SGT)	0.313	.149	.042	0.295	.215	.176
Return						
Intercept	0.082	.011	<.001	.039	.007	<.001
Sex	-0.041	.012	.001	-.014	.008	.089
α (SGT)	-0.005	.018	.767	.005	.009	.604
Risk						
Intercept	-0.073	.008	<.001	-.046	.006	<.001
Sex	0.018	.009	.044	-.002	.007	.803
α (SGT)	-0.003	.012	.836	-.002	.010	.810

Note. Condition was coded such that a 0 = friend gain/parent lose, 1 = parent gain/friend lose. Return (EV) ranged from -60 to 16.88 and SD ranged from 9.68 to 40. γ-s are fixed effects and represent expected changes in log odds. Robust standard errors are reported from a population-average model. α refers to the parent-friend value weighting metric from the reinforcement learning model fit to the SGT. Sex was coded 0 = male; 1 = female. *N* = 43 for Panel A results; *N* = 74 for Panel B results

Table 4. Self-other similarity values (LTJT) as moderators of parent-preference on the CCT (risk taking task). Panel A shows results from Study 1; Panel B lists results from Study 2

Predictor	A			B		
	γ	SE	*p*	γ	SE	*p*
Intercept						
Intercept	2.779	.128	<.001	1.518	.195	<.001
Sex	-0.256	.157	.110	0.191	.203	.350
Parent Sim	2.065	.479	<.001	-0.153	.513	.766
Friend Sim	-0.595	.356	.102	0.792	.654	.230
Condition						
Intercept	0.162	.094	.093	0.124	.078	.117
Sex	0.168	.105	.116	0.182	.094	.056
Parent Sim	-1.049	.305	.002	0.191	.328	.561
Friend Sim	0.547	.301	.076	-0.287	.331	.389
Return						
Intercept	0.086	.010	<.001	0.026	.006	<.001
Sex	-0.047	.011	<.001	0.005	.007	.456
Parent Sim	-0.068	.022	.004	-0.018	.022	.433
Friend Sim	0.072	.023	.004	0.000	.026	.989
Risk						
Intercept	-0.074	.008	<.001	-0.046	.004	<.001
Sex	0.019	.009	.041	0.008	.005	.100
Parent Sim	-0.042	.021	.047	-0.029	.017	.107
Friend Sim	-0.001	.019	.971	0.011	.020	.559

Note. Condition was coded such that a 0 = friend gain/parent lose, 1 = parent gain/friend lose. Return (EV) ranged from -60 to 16.88 and SD ranged from 9.68 to 40. γ-s are fixed effects and represent expected changes in log odds. Robust standard errors are reported from a population-average model. Parent Sim and Friend Sim refer to self-other similarity judgment values, computed from the LTJT task. Sex was coded 0 = male; 1 = female. *N* = 45 for Panel A results. *N* = 74 for Panel B results.

Table 5. Summary of key results across two studies

Research Question	**Study 1**	**Study 2**
Within Domain		
Do participants show a…		
Parent-over-friend preference on CCT (risk taking task)?	Yes	Yes
Parent-over-friend preference based on learning index (LI) on SGT (probabilistic learning task)?	Yes	Yes
Parent-over-friend preference in parent-friend reward weighting (α) on SGT (probabilistic learning task)?	No	Yes^{-}
Parent-over-friend preference in learning rates (λ) on the SGT (probabilistic learning task)?	No	No
Parent-over-friend preference on LTJT (self-other similarity judgment)?	Yes	No
Cross Domain		
Are the following measures related?		
Learning (LI) on the SGT; parent-over-friend preference on CCT	Friend LI – Yes Parent LI – Yes^{+}	Friend LI – Yes Parent LI – Yes
Parent-over-friend reward weighting (α) on SGT; parent-over-friend preference on CCT	Yes^{-}	No^{+}
Learning rate (λ) on SGT; parent-over-friend preference on the CCT	Friend λ – Yes^{-} Parent λ – Yes	Friend λ – No^{+} Parent λ - No
Self-other similarity (SOS) on LTJT; parent-over-friend preference on CCT	Friend SOS – Yes Parent SOS – Yes	Friend SOS – No Parent SOS – No
SGT indices (LI, α, λ); SOS on LTJT	Friend LI, α, λ – No Parent LI – Yes Parent α, λ - No	Friend LI, α, λ – No Parent LI, α, λ – No

Note. [-]indicates that result become non-significant after removing outliers/non-learners. [+]result became significant after removing outliers/non-learners. ‘Yes’, ‘No’ labels indicate the presence of statistically significant or marginally significant ($p < .10$) findings.

Supplement

Social Decision Making is Consistent Across Domains and Within Individuals

Additional Measures – Study 1

Self-Report Instruments

Sensation Seeking. Given the importance of sensation seeking for decision making behavior in this age group (Shulman et al., 2016; Steinberg et al., 2017), we collected the Brief Sensation Seeking Scale (BSSS-8; Hoyle, Stephenson, Palmgreen, Lorch, & Donohew, 2002). Using a five-point Likert scale (1 = strongly disagree, 3 = neither disagree nor agree, 5 = strongly agree), participants rated the extent to which they agreed with a series of eight items describing sensation-seeking behaviors. Sample items include "I would like to explore strange places" and "I would like to have new and exciting experiences, even if they are illegal". Responses were averaged into a single score (α: .78).

Real World Risk-Taking Behavior. We measured real world risky behavior to understand how self-oriented risk-taking related to other-oriented decision-making preferences. To this end, we administered the Domain Specific Risk-Taking Taking scale (DOSPERT; Figner & Weber, 2011) to our participants. Notably, we only used the Health and Social subscales since they constitute the most relevant domains for risk-taking in young adult participants (Mahalik et al., 2013). Participants rated the likelihood (1 = extremely unlikely, 4 = not sure, 7 = extremely likely) of engaging in 15 different health and social risk behaviors. Sample items include "Sunbathing without sunscreen", "Choosing to spend more time on a hobby than studying for school", "engaging in unprotected sex", and "disagreeing with an authority figure on a major issue". Responses were averaged into a single score (α: .70).

Perceived Stress. We collected a measure of perceived stress to potentially map how other-oriented decision-making is related to wellbeing. Participants were administered the Perceived Stress Scale (Cohen, Kamarck, & Mermelstein, 1983), which measures how often individuals presented 14 stress-related behaviors over the course of the previous month. Individuals used a five point Likert scale (1 = "never", 3 = "sometimes", 5 = "very often") to rate items such as "How often have you found you could not cope with all the things you had to do?" and "How often have you been upset because of something that happened unexpectedly?". Items were averaged into a single score after reverse scoring where appropriate; greater scores indicated higher levels of perceived stress (α: 0.84).

Emotion Regulation Tendency. Emotion regulation tendency was measured to allow for the possibility of investigating potential associations between dispositional emotion regulation use and other-oriented decision-making preferences. The traditional Emotion Regulation Questionnaire (ERQ) was administered. The ERQ taps the behavioral suppression and cognitive reappraisal strategies. The suppression subscale is comprised of four items whereas the reappraisal subscale is composed of 6. Both subscales require participants to rate their levels of agreement along a seven-point Likert scale (1 = "strongly disagree", 7 = "strongly agree"). A sample suppression item is "I control my emotions by not expressing them"; a sample reappraisal item is “When I’m faced with a stressful situation, I make myself think about it in a way that helps me stay calm”. Items within each scale are averaged together, with higher scores indicating a greater tendency to use suppression (α: .70) or reappraisal (α: .87).

Emotion Regulation Capacity. Emotion regulation capacity was measured to potentially address associations between cognitive reappraisal capacity and other-oriented decision-making preferences. We administered a version of the Emotion Regulation Questionnaire edited to address one’s ability to effectively use cognitive reappraisal (Troy, College, Ford, & Mauss, 2017). This modified version of the ERQ contains eight items about reappraisal that are similar in wording to the classic ERQ, but have been adapted to ask about one’s ability to reappraise (e.g., “When I really want to, I am very capable of controlling my emotions by changing the way I’m thinking about the situation I’m in.”). Participants rated their agree with item along a seven-point Likert scale (1 = “strongly disagree”, 7 = “strongly agree”) (α: .92).

Computerized Tasks

Alternative Other-Oriented Probabilistic Learning Task. Though the SGT had been previously used in other studies to tap social decision making in the probabilistic learning domain, we were initially concerned it would impose too many demands on participants and affect performance. We were specifically worried that presenting participants with four choice options and variable reward magnitudes (i.e., gaining/losing different amounts of points) would impinge learning and hamper task performance. To safeguard against this possibility, we pared down the SGT and administered a second, two-choice other-oriented probabilistic reversal learning task that contained only the most rudimentary elements of the SGT. This task—presented as the ‘shapes game’ to participants—featured two stimuli (⊗ and ⊠) that were associated with unique reward contingencies for one’s nominated parent friend, respectively. At any given trial, one shape would be more likely to pay out a reward for the parent and loss for the friend (70% likelihood), compared to yielding a loss for parent and reward for friend (30% likelihood). The other shape would have the opposite likelihoods (70% parent lose—friend gain, 30% parent gain—friend lose). The shapes swapped contingencies every ~35 trials (138 trials total). We obtained metrics of parent—friend preference using the same modeling procedure as used with the SGT. We ultimately favored the SGT over this alternative because several participants verbally expressed confusion during the training and testing procedure. In the interest of transparency, we report results obtained with the shapes task. The α-shapes metric was not significantly different from a null value of .5 (α-shapes mean (SD): 0.538 (0.240), $t(42) = 1.048$, $p > .250$). The α metric obtained from the SGT did not differ significantly from the one obtained with the shapes task ($t(42) = 0.6524$, $p > .250$). The learning rates (λs) for the shapes task did not significantly differ from one another (λ-parent mean (SD): 0.487 (0.32), λ-friend mean (SD): .473 (0.37)). Due to differences in the number of reversals and trials between reversals, we did not compare learning rates for parents and friends between the shapes task and the SGT. Correlations between the shapes’ α metric and self-parent similarity and self-friend similarity were also negligible (r = .116, r = -.093, respectively). Statistical relationships between behavior on this task and the CCT are presented in Supplementary Table 4.

Self-Oriented Probabilistic Learning Task. A canonical, two-choice probabilistic reversal learning task (e.g., den Ouden et al., 2013; Hanson et al., 2017), identical to the one used by Guassi Moreira and colleagues (2017), was administered to measure self-oriented probabilistic learning. Participants saw a blue and yellow slot machine on every trial and were told that the two machines differed in their likelihood of paying out (in points). Participants were notified that each machine's payout likelihood was subject to change over the course of the task, and were instructed to always pick the machine they thought was most likely to pay out. The payout likelihoods for each machine would switch between .7 and .3 approximately every 35 trials (138 total trials). Participants were not made aware of precisely when payout likelihoods would switch. A classic reinforcement learning model, a la Rescorla-Wagner (Rescorla & Wagner, 1972), was used to model the data in a manner largely consistent with our prior implementation (see Guassi Moreira, Parkinson, & Silvers, 2017). The only difference in implementation here being that instead of using grid search estimates as final metrics, we used them as starting values for optimization (via R's `optim()` function).

Trait Normalization Procedure for Lexical Trait Judgment Task Stimuli

As mentioned in the main document, one of the strengths of our LTJT stimuli were that they were generated from individuals of our target population. This bulk of this procedure was first described at length in the Supplemental Materials to Guassi Moreira et al., 2018; We recapitulate the most relevant details below and describe the additional steps taken to finalize the pool of stimuli.

We obtained the traits using the same parent—friend nomination/salience procedure from a different pool of participants in a prior other-oriented decision making study (Guassi Moreira et al., 2018). The phrases and adjectives participants used in the salience procedure were lightly curated (i.e., inappropriate/non-relevant items were removed) and posted to a HIT on Amazon's Mechnical Turk. MTurk participants (n = 110 across two sessions) were asked to "rate traits and phrases commonly used to describe individuals on how positive or negative they are". Demographics for MTurk participants, in terms of age and sex, were consistent with that of our target population (see Supplement of Guassi Moreira et al., 2018 for descriptives). Participants used a seven-point Likert scale (1 = "extremely negative", 4 = "neutral", 7 = "extremely positive"). These rated traits constituted the initial pool for LTJT stimuli. We further curated the stimuli for the LTJT by removing phrases that were long (e.g., 'tough but fair'). Next, we aggregated ratings for each item (i.e., averaged each trait's rating across MTurk participants) to yield a continuous metric of valence. Traits were then segregated into three valence categories based on cut-points (positive: 5.0-7.0; neutral: 3.1-4.9; negative: 1.0-3.0). Finally, we selected ~60 traits from each category to create two versions of the LTJT. Each version contained ~40 traits per category, which can be further subdivided into a set of common traits (traits in a category that are present in both versions of the task) and unique traits (traits that were unique to a given version). Participants were administered one of these two versions (A or B; order counterbalanced between participants).

Additional Measures – Study 2

Study 2 was conducted as part of a broader data collection effort on social decision making. A comprehensive list of additional measures and procedures of this effort are listed in a pre-registration document at osf.io/6278m

Study 2 – Hypotheses & Additional Data Collection Details

Hypotheses (reprinted from osf.io/6278m)

*If parent preferences generalize to other-oriented decision-making domains, participants should also favor parents over friends when learning about probabilistic reward contingencies.

*If parent preferences are driven by greater self-other representational overlap, then participants should evince greater self-parent representational similarity than self-friend representational similarity.

Data Collection Procedure Details

In Study 2 we added data from six hundred participants across the three experimental paradigms we previously reported. This process first began by re-purposing data from a separate, pre-registered, ongoing social decision making data collection effort in our lab (osf.io/jcme7). This data collection effort involved running participants through the risk taking, probabilistic learning, or self-other similarity judgment protocols as in Study 1. Most of these participants only completed one of these tasks, while a subset completed either both the risk taking and self-other similarity judgment tasks or both the probabilistic learning and self-other similarity judgment tasks.

To be as thorough as possible in following up on Study 1, we realized we would need to run another set of participants through both the risk taking and probabilistic learning tasks. We spent the months of May through July collecting these additional data. Notably, because some these data were collected as part of a broader social decision making data collection effort, we collected additional measures to answer additional questions. Although such questions are related to the topic covered in this manuscript, they are ultimately outside its scope and results are thus not reported. A full list of measures in the pre-registered for the aforementioned data collection effort's pre-registration (osf.io/6278m).

This means that some data from Study 2 are publicly available at osf.io/d42ar (the OSF project for the separate social decision making data collection effort that partially ended up comprising some of Study 2) and the rest of the data, those pertaining to cross-domain comparisons of CCT and SGT, are kept in the original OSF project for this study (osf.io/534mz). To recapitulate:

Some of Study 2's data come from a separate data collection effort. Participants were administered the CCT, SGT, and LTJT. Some participants were administered only 1 of these tasks, others were administered the CCT & LTJT and others were administered the SGT & LTJT. To obtain data for a CCT & SGT comparison, we went through with an additional data collection period.

Study 2 Additional Analysis Notes - Excluding LTJT Non-Responders

Participants were instructed to skip a word on the LTJT if they did now know what it meant. A small subset of participants skipped many words. We re-ran our analyses without these subjects to see if these subjects were potentially driving null effects (i.e., they had noisier estimates of self-other representational similarity that were affecting the analyses). We arbitrarily set the missing data threshold at 30+ words and did not test other thresholds. Notably, this check was not done in Study 1 in hopes of having the largest possible N for analysis. Our results remained unchanged when re-running the analysis excluding participants who skipped 30+ trials[1] (N=203; Mean (SD)-Parent: 0.717 (0.13); Mean (SD)-Friend: .712 (0.14); $t(202) = 0.455$, $p > .250$, Cohen's $d = 0.032$).

Additional General Notes

Software

All random coefficient regression analyses were run in the HLM for Windows software package (version 6.06; Raudenbush, 2004; Raudenbush & Byrk, 2002). All computational behavioral modeling was conducted in the R software package (version 3.3.2). Correlations and t-tests were run using IBM's SPSS Statistics (version 24). Plots were created using the `matplotlib` library in Python (version 2.7)

[1] This type of data QA was not done in Study 1 in hopes of having the largest possible *N* for analysis.

Supplementary Table 1. Learning rate values (SGT, probabilistic learning task) as moderators of other-oriented decision-making on the CCT (risk taking task) in Study 1.

	A			*B*		
Predictor	γ	SE	*p*	γ	SE	*p*
Intercept						
Intercept	2.779	.128	<.001	2.799	.125	<.001
Sex	-0.256	.157	.110	-0.232	.156	.143
λ-Parent-SGT	2.065	.479	<.001	-0.358	.184	.058
λ-Friend-SGT	-0.595	.356	.102	0.438	.213	.046
Condition						
Intercept	0.162	.094	.093	0.209	.076	.010
Sex	0.168	.105	.116	0.103	.098	.301
λ-Parent-SGT	-1.049	.305	.002	-0.452	.122	.001
λ-Friend-SGT	0.547	.301	.076	-0.105	.121	.393
Return						
Intercept	0.086	.010	<.001	0.079	.010	<.001
Sex	-0.047	.011	<.001	-0.038	.011	.002
λ-Parent-SGT	-0.068	.022	.004	0.015	.013	.237
λ-Friend-SGT	0.072	.023	.004	0.007	.014	.632
Risk						
Intercept	-0.074	.008	<.001	-0.074	.007	<.001
Sex	0.019	.009	.041	0.016	.008	.056
λ-Parent-SGT	-0.042	.021	.047	0.007	.011	.520
λ-Friend-SGT	-0.001	.019	.971	-0.013	.009	.174

Note. Sex was coded male=0, female = 1. Condition was coded such that a 0 = friend gain/parent lose, 1 = parent gain/friend lose. Return (EV) ranged from -60 to 16.88 and SD ranged from 9.68 to 40. γ-s are fixed effects and represent expected changes in log odds. Robust standard errors are reported from a population-average model. Panel A N = 45, Panel B N = 43. *Ns* differ due to outliers/non-learners. See main text for details.

Supplementary Table 2. Real-world risk-taking (DOSPERT) and sensation-seeking (BSSS) as moderators of other-oriented decision-making on the CCT (risk taking task) in Study 1.

Predictor	γ	SE	*p*
Intercept			
Intercept	2.745	.148	<.001
Sex	-0.267	.177	.139
DOSPERT	-0.058	.093	.535
BSSS	-0.144	.129	.272
Condition			
Intercept	0.151	.085	.080
Sex	0.231	.105	.033
DOSPERT	0.024	.073	.746
BSSS	0.200	.075	.011
Return			
Intercept	0.083	.011	<.001
Sex	-0.041	.012	.001
DOSPERT	0.001	.007	.838
BSSS	0.000	.006	.943
Risk			
Intercept	-0.072	.008	<.001
Sex	0.019	.008	.034
DOSPERT	-0.007	.005	.134
BSSS	0.016	.005	.003

Note. Condition was coded such that a 0 = friend gain/parent lose, 1 = parent gain/friend lose. Return (EV) ranged from -60 to 16.88 and SD ranged from 9.68 to 40. γ-s are fixed effects and represent expected changes in log odds. Robust standard errors are reported from a population-average model. DOSPERT refers to real-world risk-taking as assessed by the social and health subscales of the DOSPERT; BSSS refers to sensation seeking as assessed by the brief sensation seeking scale. Sex was coded 0 = male; 1 = female. *N* = 45 for this analysis.

Supplementary Table 3. Correlation matrix of Study 1 variables.

	1.	*2.*	*3.*	*4.*	*5.*	*6.*	*7.*	*8.*	*9.*	*10.*	*11.*
1. LI-Parent	1										
2. LI-Friend	.24	1									
3. α	.36*	-.17	1								
4. λ-Parent	-.21	.11	-.29	1							
5. λ-Friend	.17	.09	.59***	-.08	1						
6. Self-Par Sim	.17	.04	-.01	.27	.02	1					
7. Self-Fri Sim	.32*	-.00	.01	.16	-.24	.61***	1				
8. Parent RQ	.10	-.11	-.08	.13	-.07	.39**	.24*	1			
9. Friend RQ	-.11	.03	-.20	.22	-.42***	.27	.45**	.41**	1		
10. DOSPERT	-.06	-.06	-.01	.00	.13	-.19	-.07	-.44**	-.27	1	
11. BSSS-8	-.12	-.24	-.05	-.13	-.05	-.28	-.10	-.52***	-.40**	.53***	1

Note. *** $p < .001$, ** $p < .01$, * $p < .05$. RQ refers to relationship quality; Sim refers to self-other judgment similarity values. α refers to parent—friend reward weighting in SGT modeling; λ refers to learning rates in SGT modeling; LI refers to learning index from the SGT; Risk-Taking refers to self-reported risk-taking from the Social and Health subscales of the DOSPERT; Sen-Seek refers to self-reported sensation seeking from the BSSS-8.

Supplementary Table 4. Parent—friend weights (α panel) and learning rate values (λ panel) from the shapes task (alternative two-choice probabilistic learning task) as moderators of other-oriented decision-making on the CCT (risk taking task) in Study 1.

	α			λ			
Predictor	γ	SE	p	γ	SE	p	Predictor
Intercept							Intercept
Intercept	2.800	.148	<.001	2.749	.149	<.001	Intercept
Sex	-0.273	.180	.137	-0.261	.178	.150	Sex
α (Shapes)	0.619	.332	.069	-0.312	.241	.203	λ-Par-Shapes
	-	-	-	0.440	.268	.108	λ-Fri-Shapes
Condition							Condition
Intercept	0.101	.097	.302	0.157	.085	.071	Intercept
Sex	0.231	.118	.057	0.193	.104	.071	Sex
α (Shapes)	-0.479	.211	.028	0.237	.175	.184	λ-Par-Shapes
	-	-	-	-0.469	.164	.007	λ-Fri-Shapes
Return							Return
Intercept	0.081	.010	<.001	0.080	.010	<.001	Intercept
Sex	-0.040	.011	<.001	-0.039	.011	.002	Sex
α (Shapes)	-0.003	.020	.897	0.006	.019	.769	λ-Par-Shapes
	-	-	-	0.007	.013	.561	λ-Fri-Shapes
Risk							Risk
Intercept	-0.073	.007	<.001	-0.073	.007	<.001	Intercept
Sex	0.016	.008	.060	0.019	.008	.026	Sex
α (Shapes)	-0.006	.018	.757	0.023	.013	.093	λ-Par-Shapes
	-	-	-	-0.038	.011	.002	λ-Fri-Shapes

Note. Sex was coded male=0, female = 1. Condition was coded such that a 0 = friend gain/parent lose, 1 = parent gain/friend lose. Return (EV) ranged from -60 to 16.88 and SD ranged from 9.68 to 40. γ-s are fixed effects and represent expected changes in log odds. α refers to the parent-friend value weighting metric from the reinforcement learning model fit to the shapes task. λ refers to parent and friend (respectively) learning rates from the reinforcement learning model fit to the shapes task. Robust standard errors are reported from a population-average model.

Supplementary Table 5. Learning indices (SGT, probabilistic learning task) as moderators of social decision making preferences on the CCT (risk taking task) excluding non-learning outliers. Panel A contains results for Study 1, Panel B contains results for Study 2.

Predictor	*A*			*B*		
	γ	SE	*p*	γ	SE	*p*
Intercept						
Intercept	2.829	.135	<.001	1.792	.141	<.001
Sex	-0.296	.165	.081	-0.340	.188	.078
LI-Parent	0.005	.004	.263	-0.008	.006	.185
LI-Friend	0.003	.003	.371	0.008	.005	.074
Condition						
Intercept	0.089	.073	.230	0.312	.061	<.001
Sex	0.216	.095	.028	0.074	.083	.380
LI-Parent	0.004	.002	.094	0.009	.004	.052
LI-Friend	-0.008	.002	.001	-0.009	.004	.018
Return						
Intercept	0.081	.009	<.001	0.052	.006	<.001
Sex	-0.039	.011	.001	-0.025	.008	.003
LI-Parent	-0.001	.000	.050	0.000	.000	.689
LI-Friend	0.004	.000	.007	0.000	.000	.654
Risk						
Intercept	-0.074	.007	<.001	-0.064	.009	<.001
Sex	0.018	.008	.039	0.010	.010	.296
LI-Parent	-0.000	.000	.255	-0.000	.000	.078
LI-Friend	-0.000	.000	.729	0.000	.000	.822

Note. Condition was coded such that a 0 = friend gain/parent lose, 1 = parent gain/friend lose. Return (EV) ranged from -60 to 16.88 and SD ranged from 9.68 to 40. γ-s are fixed effects and represent expected changes in log odds. Robust standard errors are reported from a population-average model. α refers to the parent-friend value weighting metric from the reinforcement learning model fit to the SGT. Sex was coded 0 = male; 1 = female. Panel A *N* = 43, Panel B *N* = 41. *N*s differ to exclusion of outliers/non-learners. See main text for details.

Supplementary Table 6. Alpha values (SGT; probabilistic learning task) as moderators of social decision making preferences on the CCT (risk taking task) excluding non-learning outliers. Panel A contains results for Study 1, Panel B contains results for Study 2.

Predictor	*A*			*B*		
	γ	SE	*p*	γ	SE	*p*
Intercept						
Intercept	2.740	.136	<.001	1.766	.151	<.001
Sex	-0.199	.171	.251	-0.320	.187	.095
α (SGT)	0.281	.317	.381	-0.423	.592	0.479
Condition						
Intercept	0.139	.088	.121	0.417	.084	<.001
Sex	0.186	.108	.093	-0.035	.075	.641
α (SGT)	0.252	.163	.131	0.908	.486	.069
Return						
Intercept	0.081	.010	<.001	.053	.007	<.001
Sex	-0.041	.012	.002	-.025	.008	.006
α (SGT)	-0.008	.020	.687	-.003	.018	.890
Risk						
Intercept	-0.072	.007	<.001	-.063	.009	<.001
Sex	0.015	.008	.090	.010	.010	.340
α (SGT)	-0.016	.012	.186	-.008	.014	.568

Note. Condition was coded such that a 0 = friend gain/parent lose, 1 = parent gain/friend lose. Return (EV) ranged from -60 to 16.88 and SD ranged from 9.68 to 40. γ-s are fixed effects and represent expected changes in log odds. Robust standard errors are reported from a population-average model. α refers to the parent-friend value weighting metric from the reinforcement learning model fit to the SGT. Sex was coded 0 = male; 1 = female. Panel A N = 45, Panel B *N* = 41. *N*s differ to exclusion of non-learners/outliers. See main text for details.

Supplementary Table 7. Learning rate values (SGT, probabilistic learning task) as moderators of other-oriented decision-making on the CCT (risk taking task) in Study 2.Panel A contains results including outliers, Panel B contains results excluding outliers.

	A			*B*		
Predictor	γ	SE	*p*	γ	SE	*p*
Intercept						
Intercept	1.668	.108	<.001	1.801	.125	<.001
Sex	-0.052	.140	.709	-0.386	.172	.031
λ-Parent-SGT	0.012	.131	.929	0.158	.240	.515
λ-Friend-SGT	0.120	.136	.380	0.232	.189	.228
Condition						
Intercept	0.300	.089	.002	0.306	.068	<.001
Sex	0.074	.108	.494	0.115	.106	.283
λ-Parent-SGT	-0.126	.100	.214	-0.255	.178	.161
λ-Friend-SGT	-0.086	.095	.367	-0.232	.098	.024
Return						
Intercept	0.037	.007	<.001	0.051	.006	<.001
Sex	-0.012	.007	.121	-0.024	.007	.003
λ-Parent-SGT	0.023	.009	.010	0.004	.011	.744
λ-Friend-SGT	0.009	.007	.199	0.005	.009	.582
Risk						
Intercept	-0.045	.006	<.001	-0.059	.008	<.001
Sex	-0.003	.006	.041	0.005	.009	.563
λ-Parent-SGT	-0.015	.009	.047	-0.016	.011	.152
λ-Friend-SGT	-0.002	.007	.971	0.009	.008	.260

Note. Sex was coded male=0, female = 1. Condition was coded such that a 0 = friend gain/parent lose, 1 = parent gain/friend lose. Return (EV) ranged from -60 to 16.88 and SD ranged from 9.68 to 40. γ-s are fixed effects and represent expected changes in log odds. Robust standard errors are reported from a population-average model. Panel A N = 74; Panel B N = 41. *Ns* differ due to exclusion of outliers/non-learners. See main text for details.